Effects of Soil Properties on the Corrosion Progress of X70-Carbon Steel in Tropical Region

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This research aims to investigate the influence of soil engineering properties on the corrosion dynamic and to classify the soil engineering properties according to the power law constants *k* and *v*. The study focuses on four soil engineering properties: moisture content, clay content, plasticity index, and particle size. Fieldwork and laboratory tests were carried out to measure the metal loss influenced by soil properties. Results from fieldwork indicated moisture content as the most influential factor on metal loss. Principal component analysis classified moisture content into metal loss constant *k*, while plasticity index and particle size are grouped into corrosion growth pattern constant *v*. Similar findings were also observed for results from laboratory tests. As a conclusion, this research has identified moisture content as the most significant governing factor on metal loss constant *k*, while other soil properties have strong to modest influence on corrosion growth constant *v*. This research also reveals the existence of an optimum value of soil properties that influence the highest measured corrosion rate. This finding is significant and may change the way researcher model corrosion behaviour.

Keywords: Underground corrosion; soil; pipeline; carbon steel; parametric study

1. Introduction

Corrosion as one of the major causes of pipeline failure has received great attention among various parties, especially pipeline owners (Sosa and Alvarez-Ramirez 2009; Mohd et al. 2014; Tahir et al. 2015a). Research to obtain a better understanding of the cause of corrosion is continuously carried out and serves as the foundation of reducing pipeline failures. Underground pipelines are laid across various types of soil environments with different degrees of corrosivity. These various surroundings and conditions may contribute to failures in coating, inhibitors, or cathodic protection. Even though maintenance is done regularly, pipelines still face corrosion attacks due to corrosive environments that surround the structure (Peabody 2011; Wang et al. 2011;

Noor et al. 2012a; Tahir et al. 2015b).

Soil engineering properties and soil content are important parameters that may have some influence on the corrosion dynamic of buried pipelines. The problem is that these factors do not affect the pipeline equally at all locations, and hence, corrosion defects do not grow at the same rate throughout the length of the pipeline. If the operators can identify those corrosion defects that are active and the factors that influence the corrosion rate, then predictions of future corrosion severity for each and every defect can be made.

Earlier research has performed extensive modelling of corrosion in soil by incorporating a wide range of soil parameters including soil contents and soil properties. The parameters that were found to have governance on the corrosion dynamic were then used to develop a predictive corrosion model. Even though a wide range of soil parameters was included in the corrosion model development, soil engineering properties did not receive sufficient attention, as can be seen in the previous research (Doyle et al. 2003; Bullard et al. 2003; Alamilla et al. 2009). This may be due to an assumption that these parameters do not govern the rate of metal loss underground. However, the assumption is not backed by strong empirical proof. If the governance of these parameters can be proven, its inclusion in the future corrosion model will become necessary.

Previous works on corrosion modelling for underground surroundings leaned towards corrosion progress based on power law patterns. The development of established predictive models was initially motivated by the work of Romanoff (1957), who modelled corrosion growth using power law principles based on a 17-year collection of corrosion data of buried ferrous pipelines in a wide range of soil as follows:

$$d_{max} = kt^{v} \qquad (1)$$

where d_{max} represents maximum pit depth, t is exposure time, and k and v are constant regression parameters.

In order to utilise the power law model, parameters that contribute towards corrosion dynamic must be classified into two groups of constants, namely metal loss constant (k) and corrosion growth pattern over time (v). Rossum (1969) later derived a corrosion model and found common agreement with the model proposed by Romanoff (1957). He mentioned that the constant v depends on the state of aeration, resembling the power law model. He further discussed the role of several factors that influence corrosion dynamics and are related to soil resistivity, soil aeration, pH, and cell potential. Mughahghab and Sullivan (1989) continued the effort and further investigated the dependency of the constants k and v on the related soil parameters. They found that k is primarily determined by soil pH and resistivity, while v is a function of moisture content and clay fraction.

Several new generations of statistical models for pitting depth have been proposed recently (Katano et al. 2003; Li 2003; Velázquez et al. 2009, 2010). Katano et al. (2003) conducted a study at five sites in Japan. A total of 883 samples of maximum pit depth and 17 environmental parameters were collected to perform a multivariate regression analysis. An empirical predictive model was proposed based on the power law model. Katano concluded that the prediction model of maximum pitting depth is governed by the following parameters: soil type, preparation history of land, soil resistivity, pH, redox potential, sulphides, and exposure time.

Similar to Katano et al. (2003), Li (2003) conducted research to further investigate corrosion phenomena. A total of 69 sites along the natural gas transmission polyethylene-coated carbon steel pipelines spread over Korea were investigated from

1998 to 2000. A total of 17 environmental factors were measured by collecting soil samples at sites where pit growth was observed. The installation period of these pipelines varied from two months to nearly 14 years. The main difference between the study by Li (2003) and Katano et al. (2003) was that the former explored the effect of microbiologically influenced corrosion (MIC) and determined the effect of sulphate-reducing bacteria (SRB) on the corrosion dynamic. By adapting the model proposed in Equation 2, he proposed a predictive model as follows:

$$P_{0.cal} = 0.500 P_c t^{0.372} \tag{2}$$

where $P_{0.cal}$ is the predictive pit depth value, P_c is the evaluation value of the environment, and t is exposure time. Several analyses were performed to formulate the constant, and the researcher found that seven parameters governed the P_c: the population of sulphate-reducing bacteria (*SRB*), pipe-to-soil potential (*P/S*), chloride content (Cl^-), reduction-oxidation potential (E_h), clay content (*Clay*), soil pH (*pH*), and soil resistivity (ρ). The relationship in a mathematical equation is as follows:

$$LogP_c = 0.700 + 0.069*(LogSRB) + 0.749*(P/S) + 0.203*(LogCl^-) - 0.050*(E_h x Clay) - 0.014*(pH \, x \, Log\rho) \tag{3}$$

Velázquez et al. (2009, 2010) developed a statistical model from a total of 259 soil and pipeline samples for onshore underground pipelines operating in southern Mexico. Some of those pipelines were cathodically protected others not, some were coated others not and the average age of these pipelines is 17 years. The data collected in their study included maximum pit depth (d_{max}), exposure time (t), redox potential (*rp*), pH (*pH*), pipe-to-soil potential (*pp*), soil resistivity (*re*), water content (*wc*), soil bulk density (*bd*), chloride content (*cc*), bicarbonate content (*bc*), sulphate content (*sc*), and coating type (*ct*). The soil samples collected were classified as clay (110 samples), sandy clay loam (79 samples), clay loam (61 samples), silty clay loam (6 samples), silty clay (2 samples), and silt loam (1 sample). However, only the first three soil types were found to have a significant number for statistical analysis. Therefore, 250 samples were considered in the study. For the development of a predictive pitting corrosion model, a power law principle was successfully adopted, similar to Katano (2003). A regression analysis was carried out for 1,024 possible combinations to obtain the best model, and the constants *k* and *v* were found as follows:

$$k = k_0 + k_1 rp + k_2 ph + k_3 re + k_4 cc + k_5 bc + k_6 sc \qquad (4)$$

$$v = n_0 + n_1 pp + n_2 wc + n_3 bd + n_4 ct \qquad (5)$$

According to Equation 4, the constant *k* is governed by redox potential, pH, resistivity, chloride, bicarbonate, and sulphate content. On the other hand, pipe-to-soil potential, water content, bulk density, and the coating type were found as functions to express the constant *v* (refer to Equation 5). Both coefficients for *k* and *v* are dependent on three dominant soil types: clay, sandy clay loam, and clay loam. An average coefficient for all soil types was also established. The developed model based on all type of soils was used to predict the field corrosion data.

These works mainly focused on the statistical relationship between soil properties and metal weight loss over time to group the parameters under constants *k* or *v* according to the power law. The studies were conducted at real sites and lacked investigation of the individual performance of each parameter on corrosion progress. The correlation between soil parameters and metal weight loss was based on statistical inference through multi-regression since corrosion in soil is mathematically influenced by so many factors. Hence, individual performance of each soil parameter on metal weight loss based on parametric study was not feasible since the intensity of the parameters could not be controlled on site in order to observe the change in the metal loss rate relative to variations of soil parameter intensity. This makes the single correlation between selected soil parameters and metal weight loss from on-site results prone to errors since a real environment is very random and unpredictable. Hence, this may jeopardise the accurate classification of soil parameters in the right groups between both constants *k* and *v*.

A parametric study using a one-factor-at-a-time approach (OFAT) may give a window of opportunity to accurately classify the influence of soil properties on either metal loss (*k*) or the pattern of corrosion growth over time (*v*) according to the power law. The OFAT approach allows modification of only a single factor at a time, which can provide better understanding of the soil properties' degree of influence on the corrosion dynamic (Frey et al. 2003). The right classification of these parameters may contribute to better corrosion model development if the corrosion progress follows the power law. For that reason, the main aim of this research is to investigate the relationship between the soil engineering properties of moisture content, plasticity index, particle size, and clay content and the corrosion dynamic as experienced by underground gas pipelines using multi-regression and OFAT approaches. By achieving the aforementioned aim, the research can classify the soil engineering properties into metal loss constant (*k*) and corrosion growth pattern over time (*v*) based on fieldwork and parametric study. The main challenge in developing a predictive corrosion model is having a better understanding of the selection of parameters to improve model accuracy. Previous research has rarely taken into account soil engineering properties in the development of corrosion models and corrosion growth projections. Thus, the outcome of this research may answer the level of influence of soil engineering properties upon the corrosion dynamic.

2. Experimental Work

Five sites located on the east coast of Peninsular Malaysia, known as SITE 1 to SITE 5, were identified for fieldwork. The experiment was carried out by exposing steel coupon to underground so that the behaviour of corrosion based on weight loss could be observed, monitored, and measured. A total of 50 steel coupons were installed per area (for SITE 2 to SITE 5) in 25 boreholes. Each borehole can house two coupons which were placed at 0.5m and 1.0m depth from ground surface. SITE 1 is located in a rocky area and mainly consist gravel soil (hard surface). Hence, the drilling process only managed to provide seven boreholes with only one coupon installed per hole at a depth of 0.3m to 0.5m depth from the ground surface. For every three months, eight coupons from four holes were dug out randomly to measure the average metal weight loss (for SITE 2 to SITE 5) while for SITE 1, only one coupon was dug out per visit. Soil sampling was carried out at each hole right after coupon retrieval to conduct parameter testing. The field work was completed in the period of 18 months with total of 188 coupons retrieved from the five areas. The fieldwork was designed to produce information regarding the weight loss of buried steel coupon subject to the corrosion process. The information on weight loss was then correlated with the measured parameters of moisture content, clay content, plasticity index, and particle size using an all-factors-at-a-time (AFAT) approach.

Laboratory tests were conducted according to ASTM G162-99 (ASTM 2010). The laboratory test (parametric study) functions as a useful tool in manipulating the intensity of the aforementioned soil parameters under a controlled environment by using the OFAT method. Washed sand of medium size was used as the main medium and control sample to conduct the test. The washed sand was found to be non-plastic (plasticity index = 0) and have no clay particle. (clay content = 0%). Moisture in washed sand was removed via oven-dry method (0% of moisture content). De-ionized water was added into washed sand as the main source of moisture to manipulate the moisture content range, from 5%to 35%. Plasticity index was modified by mixing washed sand and bentonite to produce a sample with plasticity index ranging from 15 to 60. Dry sieving method was used to segregate washed sand into various particle sizes to produce four soil samples with different average of particle size distribution, from 0.045mm to 0.644mm. Kaolin clay was added proportionally (by weight) into washed sand to modify the intensity of clay content, ranging from 25% to 100%. Even though parameters of particle size and clay content seems like interconnected, however the influence of both can be differ where the former affect mainly the aeration while the latter playing the role of destruction of pipeline protection layer. All modified soil samples were then kept in a plastic container whereby steel coupon was installed in the container and placed in the mid-depth of the soil samples. The parametric performance of every single parameter with different intensities upon corrosion (weight loss) can be individually measured to support the findings from the fieldwork. A series of measurements were conducted on the steel coupon throughout the 12-month period with a total of 330 steel coupons were successfully retrieved.

Periodic retrieval was done every 3 months and 2 months for fieldwork and laboratory tests respectively. In order to get time-function data for metal weight loss, every single steel sample was assumed to be uniform in terms of strength and corrosion resistance. Hence, metal weight loss measurements from respective retrievals at different times within the testing period were considered correlated with each other.

Statistical techniques were utilized to analyse corrosion and soil parameters. A single regression (linear and power law) was applied to observe the corrosion growth pattern. Possible erroneous data due to intolerable value (extreme data) was removed using a box plot method. A normality test was performed to justify the type of correlation test. A simple linear regression analysis was used to study the relationship between metal weight loss and soil parameters. The determination of soil parameter influence upon metal weight loss and corrosion growth pattern over time was based on a principal component analysis and a paired t-test.

The coupons utilised in this research were X70 carbon steel pipes sourced from an actual pipeline segment. The pipes were machined into smaller sizes by a hot cut method. A cold cut method was then applied to remove the heat-affected zone (HAZ) on the coupon, which may cause changes in properties of the material and affect the corrosion rate (Yahaya et al. 2011; Ren et al. 2012; Noor et al. 2012b). Pipes were cut into the desired sizes for fieldwork (60 mm x 80 mm) and laboratory tests (20 mm x 30 mm). Coatings of those samples were removed to avoid inconsistent coating protection that may lead to unfair results as well as to let the coupon corrode under a worst-case scenario. The samples were thoroughly cleaned by acetone, dried, and carefully kept in a sealed plastic beg before testing to avoid any contamination, atmospheric corrosion, or any possible entities that may affect the corrosion process. The weight of each coupon (known as initial weight, W_0) was recorded so that the total weight loss after corrosion initiation could be identified.

This study focused on general corrosion; hence no investigation was done for localized corrosion. All retrieved coupons from fieldwork and laboratory tests were cleaned to determine the metal loss by weight due to the corrosion process. The cleaning procedure to remove corrosion products followed the procedure as stated in

ASTM G1-03 (ASTM 2004). Soil sampling was carried out after coupon retrieval to conduct parameter testing according to BS 1377: 1990 (BSI 1998).

3. Results of Fieldwork (AFAT Approach)

In this study, metal weight loss *(ML_F)* as a result of corrosion with specific exposure time *(T_F)* was the dependent parameter controlled by a set of independent parameters, which were moisture content (MC_F), clay content (CC_F), plasticity index (PI_F), and particle size (PS_F). Metal loss data was plotted against time of exposure to determine the pattern of corrosion dynamic for each site (refer to Figures 1 to 5). From the observations, most of the sites showed a linear (solid line) to power law pattern (dotted line) in the increment of metal loss over time. Both models showed a high coefficient of determination for the linear model (R^2 = 0.739 to 0.937) and the power law model (R^2 = 0.864 to 0.978). Based on the R^2 value, the power law model was found more feasible to represent the progress of metal loss due to corrosion over time as opposed to the linear model for most of the sites.

The normality test was carried out using Shapiro–Wilk (S–W) and Kolmogorov–Smirnov (K–S) tests (SPSS 2007). The tests were conducted at 95% confidence intervals, and the results are presented in Table 1. The corrosion data is regarded as normally distributed if the significant value (*Sig*.) is greater than 0.05 for S–W, and it is marked with an asterisk (*) for the K–S test. The results from both tests show that only moisture content has the potential to be normally distributed. This result gives important information for the following analysis, such as the correlation test.

Erroneous data/outliers such as negative growth rate or extremely high growth rate, which is highly sensitive to the change of weight before and after installation, may influence the outcome of this research. Thus, a box plot was utilised to dampen the effects on overall results. There were four measurements of metal loss, one clay content, and two plasticity indexes classified as outliers. These data sets were removed since they could affect the accuracy of the correlation analysis.

Figure 6 indicates the correlation between moisture content and metal loss. Even though the regression of coefficient (R^2) yielded a small value; due to the randomness of the real and uncontrolled environment as compared to laboratory testing, a modest correlation can be justified. This is according to Volk (1980), where an R^2 value of approximately 0.4 is considered reliable for a sample size of about 25. In general, metal loss increases with an increase in moisture content. On the other hand, clay content influences metal loss in the opposite way as compared to moisture content even though the R^2 yields an unconvincingly small value, thus showing a weak relationship (refer to Figure 7). Figures 8 and 9 show the influence of plasticity index and particle size, respectively, on metal loss. The positive trend shows that metal loss increases with the increase in plasticity index and particle size. Yet, similar to clay content, the R^2 value was too low to enable the identification of the degree of correlation between those parameters.

Tables 2 and 3 show the coefficient of correlation for Pearson and Spearman's rho correlation test between each parameter (metal loss and soil properties). These coefficients indicate the degree to which two parameters act independently of one another. Values of 1.0 or –1.0 indicate perfect positive or negative correlation respectively, while a value of zero indicates an absolutely random relationship or no correlation between two parameters. Results of both tests (refer to Tables 2 and 3) show that only metal loss (ML_F) and moisture content (MC_F) are significantly correlated. This gives an early indication that the moisture content is the only potential parameter that may govern the metal loss process. The results show some degree of agreement with simple linear regression tests (refer to Figures 6 to 9), whereby moisture content has the highest R^2 among all corrosion parameters.

Principal component analysis (PCA) is widely used in statistics, signal processing, and neural computing (Xu and Yuile 1995; Hyvarinen 1999) to reduce the number of variables in the database and to detect structure in the relationships between variables, that is, to classify variables. PCA is used to determine more precisely the controlling factors that affect corrosion dynamic in terms of metal loss (k) and time factor (v) as found in the power law equation (Li 2003). Soil properties that have a strong influence on k will affect the metal weight loss, whereas the influence on v may indicate the controlling effect of soil properties upon the growth pattern or acceleration behaviour of metal loss over time. The acceleration behaviour will distinguish between linear and power law growth patterns.

PCA was performed on two sets of parameters that relate the influence of soil properties on either metal loss (k) or corrosion growth patterns (v). Figures 10 and 11 graphically show the relationship among parameters obtained by PCA for metal loss and corrosion growth patterns respectively. The factor loadings are presented in Tables 4 and 5 for both metal loss and corrosion growth patterns respectively. The factor loading determines the contribution of each variable in the particular extracted component. Typically, Component 1 will explain the most variance as compared to other components. Hence, variables falling in Component 1 will be the controlling factors, i.e., metal loss.

The results show that metal loss and moisture content with the largest squared cosine fall in Component 1, particle size and plasticity index in Component 2, while clay content belongs to Component 3 (refer to Table 4). The squared cosine value was used to classify the variables into their particular components. This result indicates that moisture content appears to be the controlling factor on metal loss, which belongs to Component 1. On the other hand, PCA results based on corrosion growth pattern *v*, of which the *v* value was obtained from an exponential factor in the power law model from Figures 1 to 5, show that plasticity index and particle size are the controlling factors due to their classification in Component 1. If the exact pattern of corrosion growth followed the power law model, plasticity index and particle size may play an important role in controlling the acceleration of metal weight loss over time. Table 6 lists the influence of soil properties on metal loss (*k*) and corrosion growth pattern (*v*) for the fieldwork.

4. Results of Laboratory Test (OFAT Approach)

The laboratory test was specifically designed to study the effects of each soil property on the corrosion dynamic at different intensities. In contrast to the fieldwork, this could be done under a controlled environment in a laboratory. Every parameter had a set of control samples. Table 7 shows the summary of soil parameters. A total of 15 samples (three samples per intensity including control samples) were retrieved at an interval of every 2 months to study corrosion behaviour as a function of parameter intensity and time of exposure. The results may give some indication of the tendency of those four parameters on either metal loss severity (*k*) or corrosion growth pattern (*v*).

Figures 12 to 15 illustrate the relationship between corrosion rate and parameter intensity with variation of time of retrieval. The figures were mainly used to identify the optimum value, if it exists, of every single soil property that may trigger the highest corrosion rate. Judging by the plotted graph, it is obvious that all parameters except plasticity index have optimum intensity related to the highest recorded corrosion rate throughout the duration of the experiment.

Figure 12 shows a consistent pattern between corrosion rate and moisture content for every exposure time. This consistent pattern yielded a trustworthy result that the influence of moisture content follows a specific trend similar to an open downward parabola shape. Similar relationship was also reported by Gupta and Gupta (1979). The critical point was recorded at 15% moisture content, which is almost half of the studied moisture content range (0% to 35%). In the first 2 months, different variations of clay content showed a constant corrosion rate, as illustrated in Figure 13. After 6 months of exposure, the effects due to variation of clay content started to become visible where an open downward parabola shape could be seen. A drastic increase was observed in clay content from 0% to 25%, yet the corrosion rate was getting slower after the critical point. The deceleration of the corrosion rate with the increase in clay content shows the potential of clay particles to reduce the corrosion risk beyond the critical value. The corrosiveness level as a function of the clay content was as follows: 25% > 50% > 75% > 100% > 0%.

Figure 14 shows no distinct pattern in the lines that represent variations of the plasticity index throughout the periodic retrieval. Nearly all lines are spread horizontally, showing that variation of soil plasticity did not post effects on the corrosion rate. Even if there are some lines showing variation in corrosion rates, the difference is not significant enough to justify the contribution of plasticity index to the corrosion process. A similar relationship was observed for particle size and moisture content. The highest corrosion rate was recorded nearly at the middle of the particle size range of 0.344 mm, which consists of 15% silt particles, 70% sand particles, and 15% gravel. The lowest corrosion rate was recorded from a sample with a particle size of 0.045 mm. This finding generally agrees with the results from the clay content, where smaller particle size tends to lower corrosion rate.

In order to investigate whether different intensities of soil parameters are influential on metal loss over time (k), a paired t-test was carried out at a confidence interval of 95%. The commonly used definition of t-test is simply comparing two means to see if they are significantly different from each other. The paired t-test was used to test the difference of means between metal loss measurements and a range of intensities of soil parameters. The null hypothesis is that there are no differences between the means, which indicates that changes in the intensity of independent parameters will not affect the metal weight loss, whereas an alternative hypothesis is vice versa. Tables 8 to 11 show the significant value of a two-tailed paired t-test result for moisture content, clay content, plasticity index, and particle size, respectively. If the significant value is greater than 0.05, the null hypothesis will be accepted. The bold values in the tables represent the significant tested pairs.

Samples with variable moisture content yielded a significant value of less than 0.05 when compared to the control sample, as presented in Table 8. This generally indicates that the presence of moisture in soil greatly affects metal loss. A comparison among variables shows that the samples with a moisture content of 5% and 35% showed no significant difference, as did those with a moisture content of 15% and 25%. The results also indicate that metal loss seems to be very sensitive to the change in moisture since the significant value for almost all tested moisture content pairs was found to be less than 0.05.

While moisture content has been proven to be influential on metal loss, clay content, on the other hand, has exhibited dissimilar behaviour. Clay content of 25% is the only variable that can be associated with metal loss progress according to its significant value, which is less than 0.05 as compared to the control sample. A similar finding was observed when comparing clay content of 25% with 50% and 75% intensity. The other clay content variables were proven to not govern the metal loss since there was no difference between the mean of metal weight loss among those variables compared to the control sample.

Contradicting the findings for moisture content, plasticity index variables in Table 10 exhibit the most consistent pattern, whereby none of the variables yielded significant values of less than 0.05 to reject the null hypothesis. The acceptance of the null hypothesis means that the variation of plasticity index does not contribute to the progress of metal loss. Table 11 shows that an average particle size of 0.344 mm consists of gravel, sand, and silt particles, and it produces a significant value less than 0.05 when compared to other particle sizes, including the control sample. The control sample, which consisted of only washed sand particles, had no difference in terms of metal loss governance with other average particle sizes except for the 0.344 mm variable.

In general, the paired t-test has explicitly explained the governance of soil properties on metal loss. From the findings, moisture content has proven its dominance in metal loss progress caused by corrosion. The variation of moisture content can influence the rate of metal loss. Unlike moisture content, the changes in other variables such as plasticity index, clay content, and particle size are not that influential except for certain levels of intensity. Plasticity index has the most consistent pattern of insignificant influence on metal loss throughout the study, be it from experimental or laboratory work.

A similar paired t-test was conducted to examine the influence of soil parameters on the constant *v*. Tables 12 to 15 show the significant value of two-tailed paired t-test results for moisture content, clay content, plasticity index, and particle size, respectively. Moisture content variables in Table 12 exhibit the most consistent pattern in which none of the tested pairs yielded significant values less than 0.05. This is in line with the findings through principal component analysis for fieldwork in which moisture content posts an influence on metal loss (*k*) but not on time factor (*v*).

On the other hand, results in Table 13 show a few significant values that are less than 0.05 for clay content. The influence was found significant in early exposure time, and the effect lessened as time progressed from 6 months onwards. Thus, it is possible that the rate of corrosion will not be much different relative to variations of clay content if the exposure period is prolonged. PCA results from fieldwork indicate that plasticity index may be one of the governing factors on the constant *v*. A stronger finding can be seen for different plasticity index values and particle sizes as compared to clay content (refer to Tables 13 to 15). More than half of the tested pairs were found to yield a significant value of less than 0.05. The time influence was observed to play a role in the early stage. Similar to the results from the sample with variations of clay content, insignificant effects were found after 6 months of exposure.

5. Discussion

For a single linear regression between metal weight loss and soil properties (refer to Figures 6 to 9), it was found that clay content is the only parameter that has a negative correlation. An increase in particle size, moisture content, and plasticity index will increase the value of metal loss. Oguzie et al. (2004) and Velázquez et al. (2009) reported that clayey soil is technically more corrosive. This may due to partially moist clay which deposited on the steel surface experienced expansion and shrinkage due to temperature changes, hence destroy the protection layer of steel surface. However, results from Li (2003) do support the findings from fieldwork. High clay content can results in low penetration of moisture and oxygen to make contact with the buried steel coupons. This directly reduces the risk of corrosion development and shows that clay can be a protection mechanism to lower the corrosion risk. Abdullayev and Lvov

(2010) in their recent study have proposed clay particles in metal coatings as a corrosion inhibitor. Moisture content poses the highest R^2 of 0.369 with a positive trend, followed by clay content, particle size, and plasticity index, as shown in Figures 6 to 9. Moisture content has a direct effect on corrosion progress since the formation of hydroxyl ions originated in water. Particle size plays an important role in allowing the participation of water and oxygen from the atmosphere into the soil (aeration behaviour), hence providing a supply for corrosion to initiate. Soil plasticity is closely related to the presence of clay and silt particles, which are capable of retaining moisture and which influence soil aeration as well as the moisture content itself. According to the negative correlation between clay content and metal loss (refer to Figure 7), plasticity index in theory is expected to behave similarly to clay content upon corrosion progress since soil plasticity is closely related to the presence of clay particles. However, the positive trend may be due to the more dominant effect of moisture content as compared to clay content.

The idea of PCA is to classify all four corrosion parameters of soil properties into the best group of power law constants k and v. The results (refer to Table 7) show that moisture content is best grouped into the metal loss constant k, while plasticity index and particle size are better suited to constant v, representing the time factor related to corrosion growth pattern. Unfortunately, clay content falls into neither the constant k nor v categories. According to the fundamental corrosion mechanism, since water is the main contributor to the formation of rust (reddish-brown ferric hydroxide), the constant supply of water is proven influential on metal loss. There is no empirical evidence from previous work that the change in moisture content would directly affect the acceleration or the slowdown of metal loss rate as time progress (constant v). However, statistical inferences from earlier works by Mughahghab and Sullivan (1989) and Velázquez et al.

(2009) strongly mentioned the association of water content with constant *v* instead of *k*. This contradictory finding may be better clarified by results from parametric study. The comparison of PCA results for particle size and plasticity index is not feasible since the early work did not cover both parameters. Rossum (1969) and Li (2003) did clarify that the constant *v* is directly associated with aeration. Since particle size and plasticity index play important roles in the aeration of soil, this proves that the classification of both parameters into the group of constant *v* is well justified. However, clay content, which initially was hypothesised as belonging to constant *v*, did not fall into any constant group even though this parameter contributes to the aeration of soil.

Similar to PCA, the purpose of a paired t-test is to classify the studied soil properties into the best group of power law constants *k* and *v* based on the OFAT approach. The results demonstrated a good agreement with the findings from the fieldwork (refer to Table 7), which show that moisture content has a good influence on constant *k* while constant *v* is strongly influenced by plasticity index and particle size. In general, this indicates that the two different approaches are reliable for parameter classification and can complement each other quite well. As discussed earlier, the findings from the fieldwork contradict to Mughahghab and Sullivan (1989) and Velázquez et al. (2009) in regards to the classification of moisture content into constant *k* or *v*. However, parametric study has confirmed the findings from the PCA on fieldwork results. Therefore, backed by evidence from the parametric study (paired t-test), moisture content is considered to be more appropriately classified under constant *k*. The results of the parametric study are more convincing since the variation of moisture content is the only factor that influences the behaviour of the corrosion process. Furthermore, the measured metal loss on site from early research may be interfered with by other unknown corrosion factors, and the application of a multiple linear regression method may not represent the real scenario. Particle size poses a minor influence on the metal loss constant *k* as compared to constant *v*. In the meantime, clay content was identified as having a minor influence on both constants *k* and *v*. This may be one of the reasons behind the elimination of clay content from both groups of constants based on the PCA of fieldwork results. According to previous work by Li (2003) and Mughahghab and Sullivan (1989), there has been a mixed opinion on the classification of clay content. Table 16 lists the comparison of soil parameters related to constants *k* and *v* between the results of this research and earlier research.

Figures 12, 13, and 15 report optimum values of 15%, 25%, and 0.344 mm for moisture content, clay content, and particle size, respectively, in regards to maximum corrosion rate. This indicates that the relationship between these three parameters and corrosion rate does not behave linearly. A second- and third-order polynomial regression can well describe the aforementioned non-linear relationship. Sufficient attention should be drawn to this optimum value since it may trigger the highest corrosion risk. According to current practice, the constants *k* and *v* in the power law model are mostly developed based on multiple linear regressions. In this practice, since the modelling of *k* and *v* are assumed to have linear correlation, the existence of optimum value (non-linear behaviour with parabolic effect) of soil properties that may influence the highest corrosion rate will affect the accuracy of the predictive model. Therefore, a multiple non-linear regression is suggested as an alternative approach to model corrosion behaviour.

6. Conclusion

The influence of soil properties upon the corrosion dynamic has been identified through fieldwork and parametric study. Both methodologies have utilised different approaches to analyse the data—AFAT and OFAT. The findings from both approaches complement each other and provide strong empirical evidence for corrosion study. The final conclusions can be drawn as follows;

(1) Moisture content has the strongest influence on metal loss caused by corrosion in soil. The other parameters produce minor effects, with plasticity index as the least influential factor. Therefore, corrosion modelling practices must take into account moisture content as one of the important parameters that control the change of corrosion in soil. Moreover, the research also reveals that soil engineering properties alone cannot accurately estimate the potential metal loss due to corrosion in soil due to the fact that other parameters especially related to soil contents may have a stronger influence.

(2) This research has successfully determined and classified soil engineering properties that influence the metal loss (constant k) and corrosion growth pattern (constant v). Moisture content was found to be well fitted to constant k while other soil properties are better classified under constant v. This research also reveals the existence of an optimum value of soil properties that influence the highest measured corrosion rate. The finding is significant and may change the way researchers model corrosion behaviour since the current practice of modelling constants k and v is based mainly on a multiple linear regression. Future research on corrosion modelling can be improved by this classification since the power law model is highly dependent on the accuracy of constants k and v.

Acknowledgments

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Table

Table 1: Tests of normality for fieldwork

Parameters	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Metal Loss (ML_F)	.249	30	.000	.759	30	.000
Moisture Content (MC_F)	.108	30	.200*	**.954**	**30**	**.211**
Clay Content (CC_F)	.194	30	.005	.745	30	.000
Plasticity Index (PI_F)	.168	30	.031	.906	30	.012
Particle Size (PS_F)	.149	30	.089	.914	30	.018

Table 2: Pearson correlation test for fieldwork

	ML_F	MC_F	CC_F	PI_F	PS_F
ML_F	1	**0.406****	-0.179	0.089	-0.115
MC_F		1	-0.040	0.004	-0.207
CC_F			1	0.187	-0.028
PI_F				1	0.186
PS_F					1

** *Indicates significant correlation.*

Table 3: Spearman's rho correlation test for fieldwork

	ML_F	MC_F	CC_F	PI_F	PS_F
ML_F	1	**0.586****	-0.273	0.130	0.178
MC_F		1	-0.040	0.051	-0.278
CC_F			1	0.250	-0.030
PI_F				1	0.256
PS_F					1

** *Indicates significant correlation.*

Table 4: Factor loadings of metal loss for fieldwork

	Component		
	1	2	3
MC_F	**.860**	-.163	.372
ML_F	**.854**	.382	.059
PS_F	-.149	**.836**	-.297
PI_F	-.118	**.730**	.452
CC_F	-.457	-.055	**.791**

Table 5: Factor loadings of exposure time for fieldwork

	Component		
	1	2	3
T_F	**.752**	.370	.228
PI_F	**.724**	.153	.039
PS_F	**.717**	-.453	.288
MC_F	-.277	**.774**	.501
CC_F	.339	.442	**-.788**

Table 6: Summary of classification test for fieldwork

	Constant of power law model	
	Metal loss (*k*)	**Time factor (*v*)**
Controlling factor	Moisture content	Plasticity index Particle size

Table 7: Summary of soil parameters for laboratory test

Soil Parameter	**Intensity**	**Control Sample**	**Remarks**
Moisture Content (%)	5,15, 25, 35	0	Deionized water was used to change the intensity.
Clay Content (%)	25, 50, 75, 100	0	Kaolin clay was used to change the intensity.
Plasticity Index	15, 30, 45, 60	0 (Non-plastic soil)	Bentonite was used to change the intensity.
Particle Size (mm)	0.045, 0.344, 0.644	0.063 (sand only)	Dry sieving method on washed sand was used to change the intensity.

* *Intensity is a range of value for independent parameters.*

Table 8: Paired t-test for different moisture content

Moisture Content	0% (control)	5%	15%	25%	35%
0% (control)	1				
5%	**0.021**	1			
15%	**0.008**	**0.008**	1		
25%	**0.001**	**0.012**	0.072	1	
35%	**0.022**	0.093	**0.007**	**0.006**	1

Table 9: Paired t-test for different clay content

Clay Content	0% (control)	25%	50%	75%	100%
0% (control)	1				
25%	**0.035**	1			
50%	0.595	**0.005**	1		
75%	0.752	**0.035**	0.506	1	
100%	0.532	0.053	0.502	0.675	1

Table 10: Paired t-test for different plasticity index

Plasticity Index	Non-Plastic (control)	15	30	45	60
Non-Plastic (control)	1				
15	0.518	1			
30	0.654	0.084	1		
45	0.932	0.341	0.625	1	
60	0.396	0.173	0.609	0.441	1

Table 11: Paired t-test for different particle size

Average Particle Size	0.063 (mm) (control)	0.045 (mm)	0.344 (mm)	0.644 (mm)
0.063 (mm) (control)	1			
0.045 (mm)	0.125	1		
0.344 (mm)	**0.014**	**0.011**	1	
0.644 (mm)	0.059	0.056	**0.011**	1

Table 12: Paired t-test for moisture content on time function

Buried Time (month)	2	4	6	8	10	12
2	1					
4	0.198	1				
6	0.110	0.113	1			
8	0.100	0.093	0.066	1		
10	0.113	0.158	0.184	0.228	1	
12	0.113	0.123	0.126	0.135	0.246	1

Table 13: Paired t-test for clay content on time function

Buried Time (month)	2	4	6	8	10	12
2	1					
4	0.182	1				
6	**0.006**	**0.026**	1			
8	**0.038**	**0.019**	0.641	1		
10	0.059	0.052	0.183	0.089	1	
12	0.051	**0.047**	0.108	0.061	0.085	1

Table 14: Paired t-test for plasticity index on time function

Buried Time (month)	2	4	6	8	10	12
2	1					
4	0.074	1				
6	**0.003**	**0.016**	1			
8	**0.005**	**0.008**	0.722	1		
10	**0.006**	**0.025**	0.177	0.406	1	
12	**0.002**	**0.001**	**0.048**	**0.042**	0.364	1

Table 15: Paired t-test for particle size on time function

Buried Time (month)	2	4	6	8	10	12
2	1					
4	0.108	1				
6	0.063	0.304	1			
8	**0.046**	0.103	0.092	1		
10	**0.004**	**0.032**	**0.042**	0.054	1	
12	**0.003**	**0.008**	**0.019**	**0.032**	0.628	1

Table 16: Summary of classification for constants *k* and *v*

Current Study	**Soil parameter related to constant *k***	**Soil parameter related to constant *v***
PCA Fieldwork	Moisture content	Plasticity index Particle size
Parametric study	Moisture content *Particle size *Clay content	Plasticity index Particle size *Clay content
Previous Researchers	**Soil parameter related to constant *k***	**Soil parameter related to constant *v***
Mughahghab and Sullivan[10]	…	Moisture content Clay content
Li[12]	Clay content	…
Velázquez[13]	…	Moisture content

** Indicates minor influence.*

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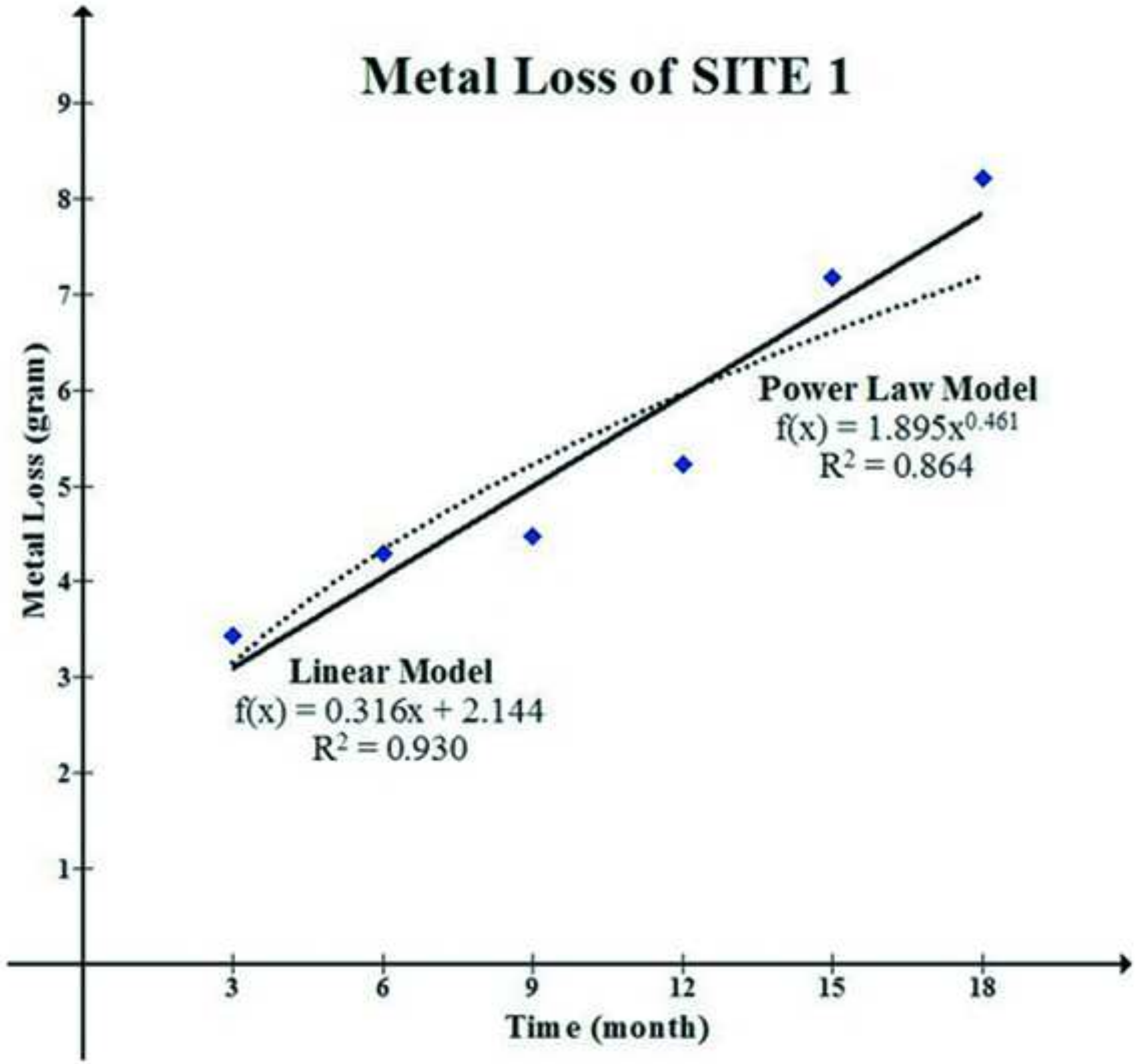

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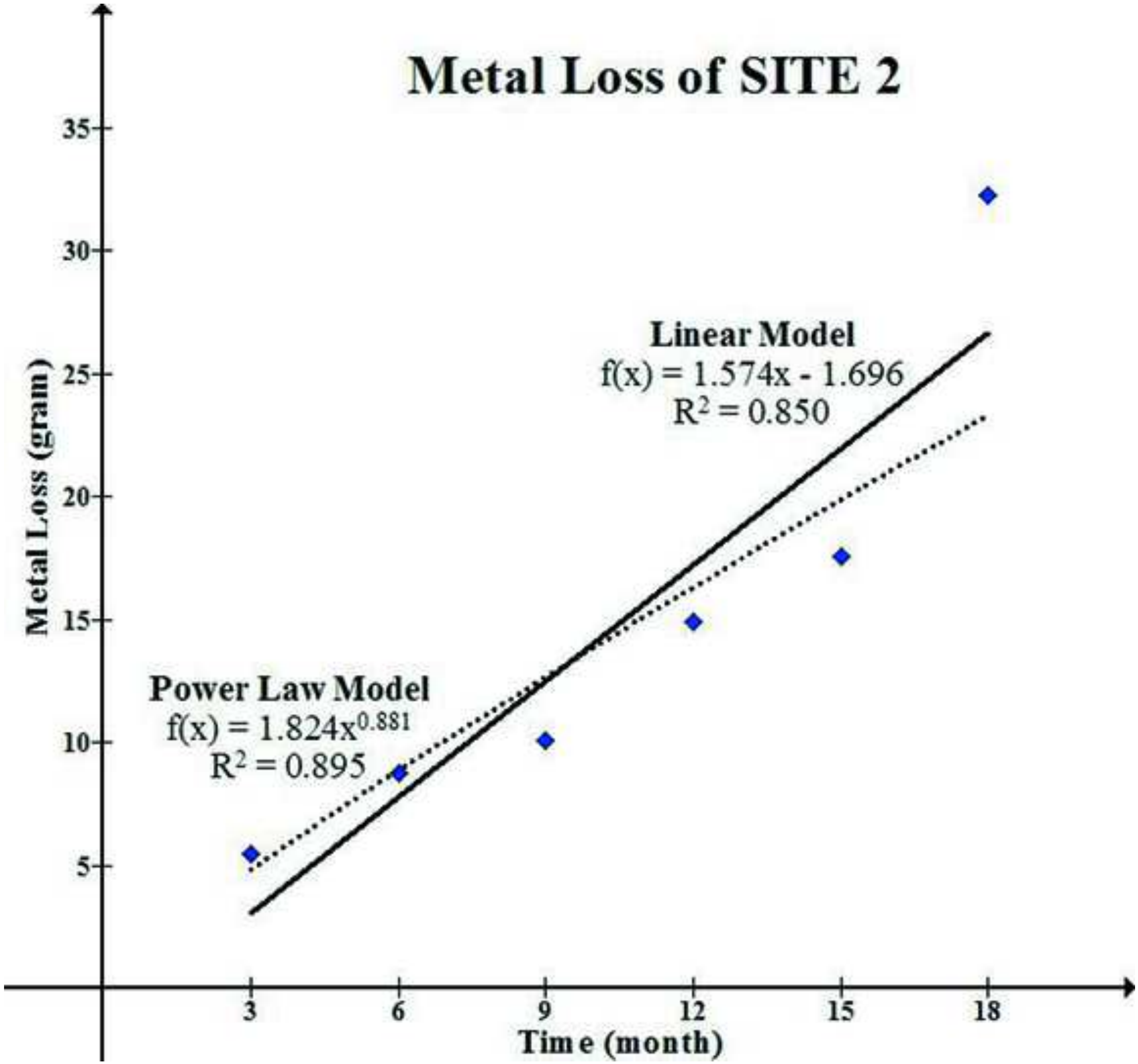

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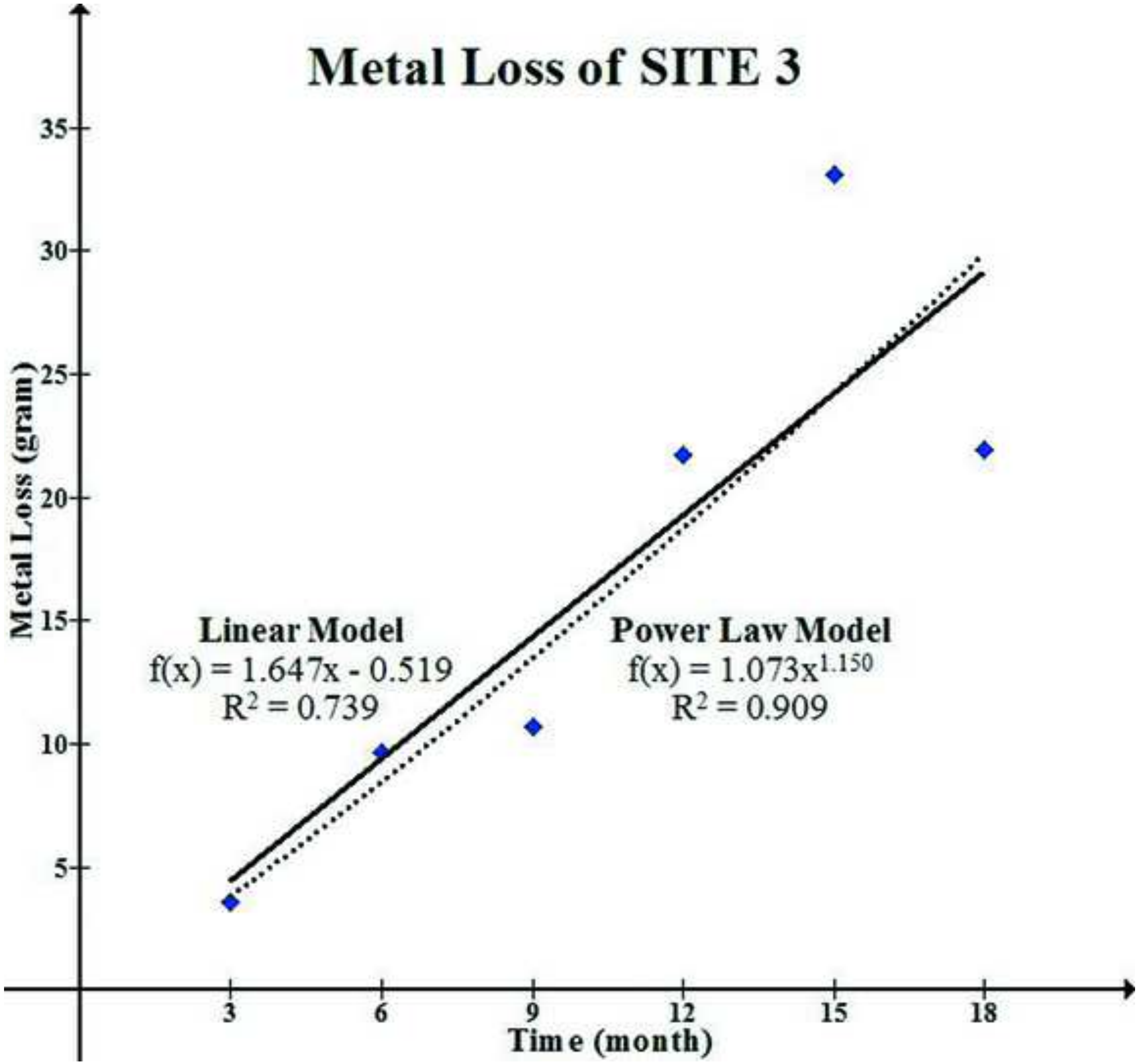

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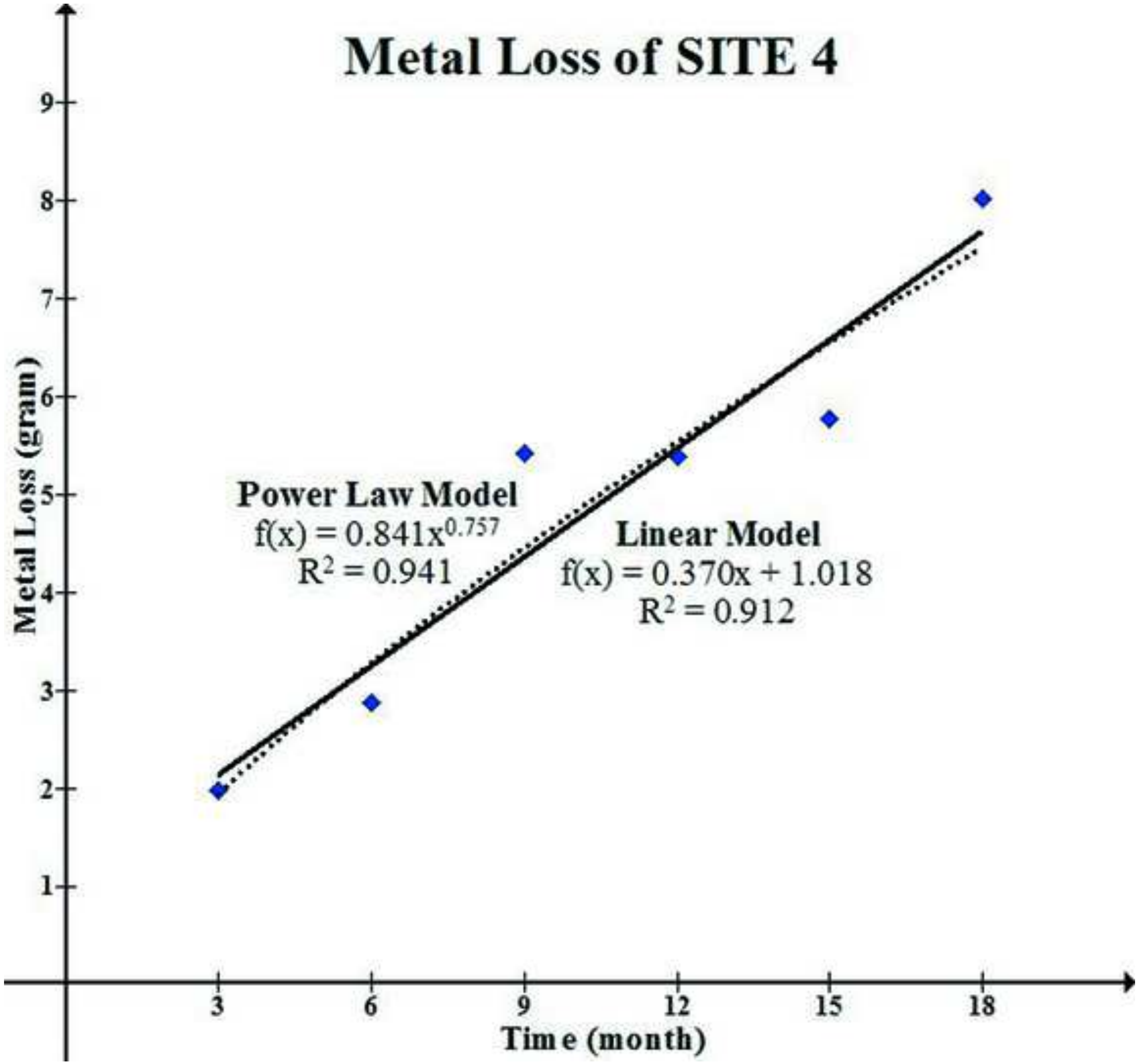

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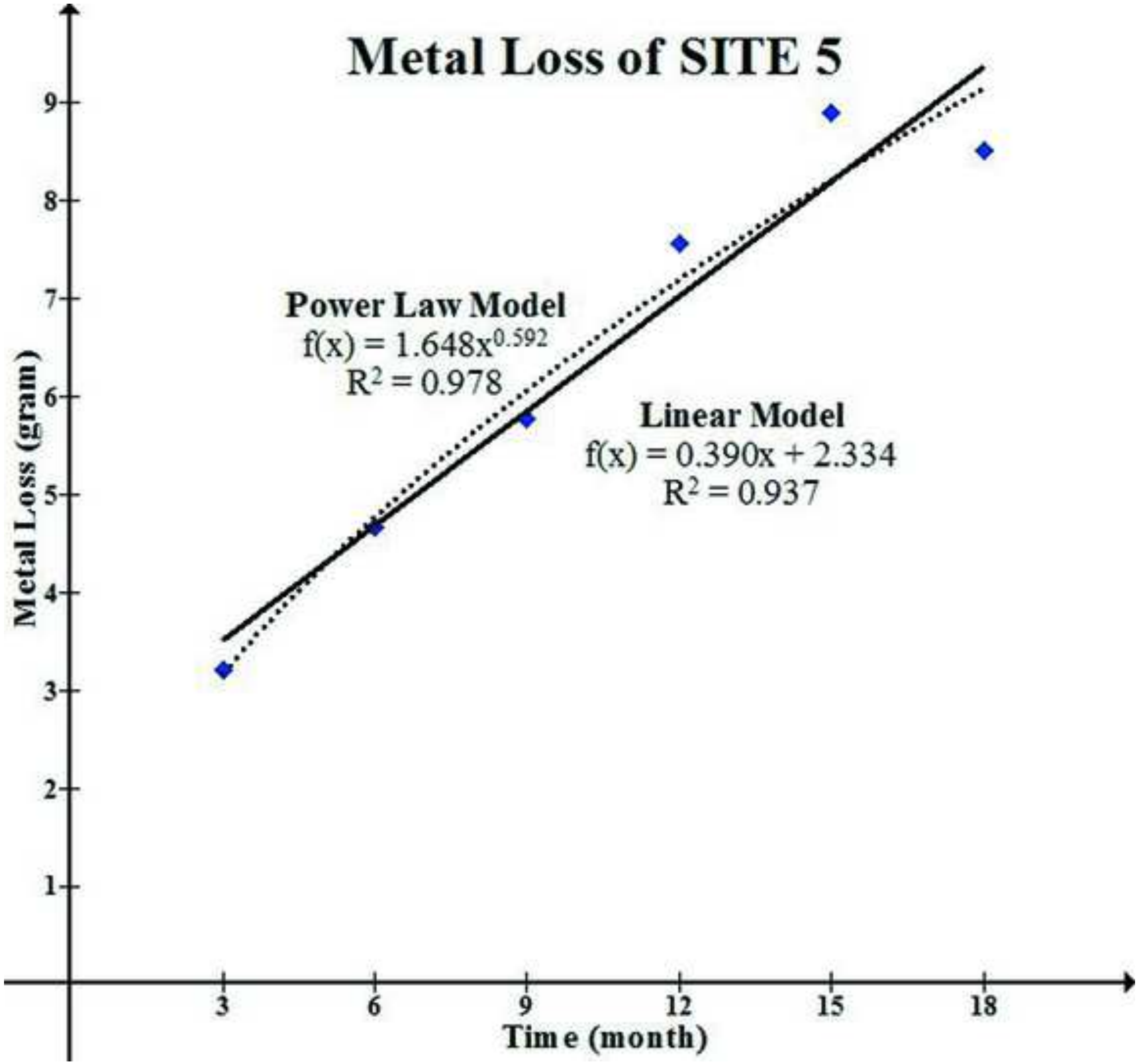

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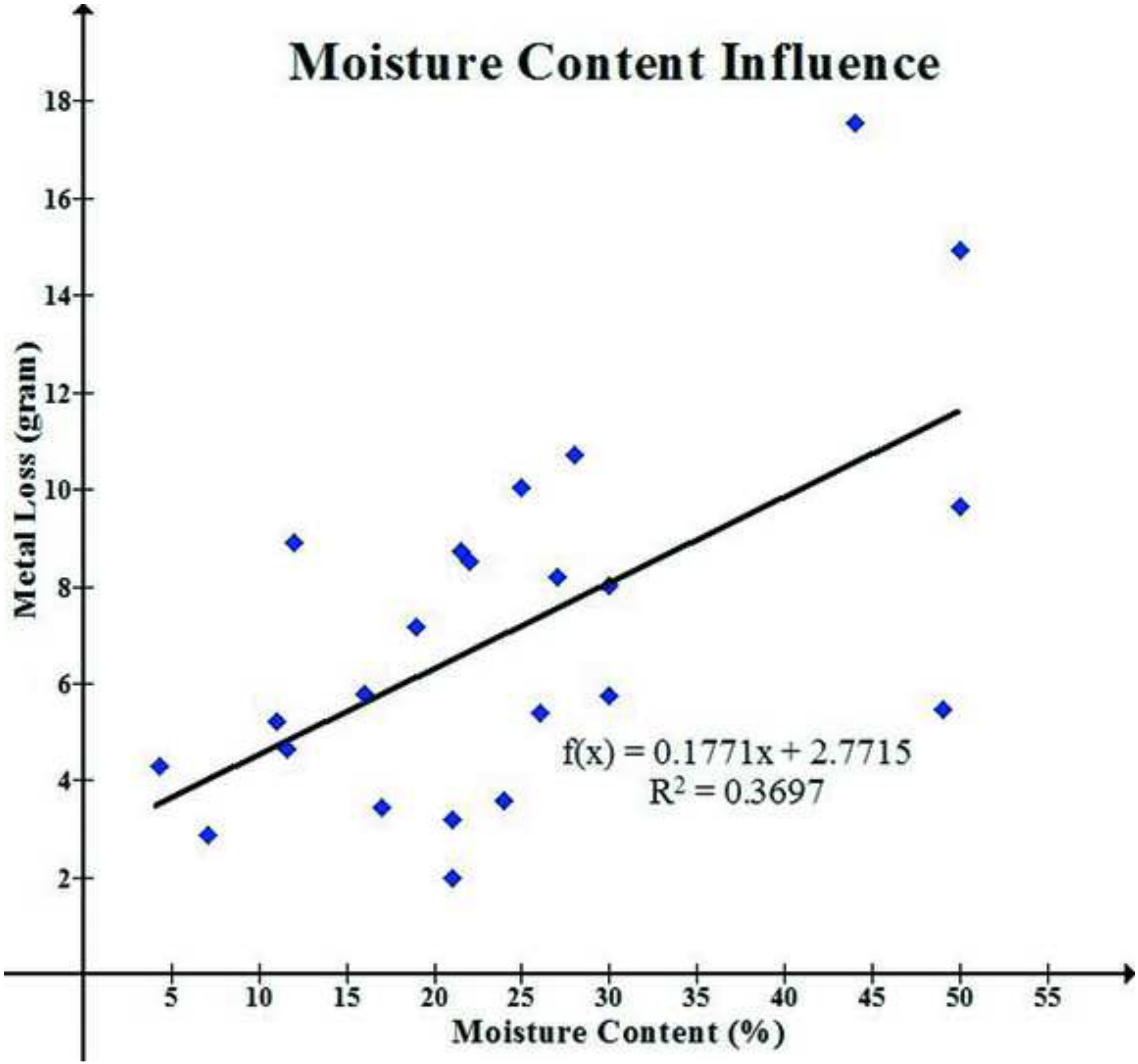

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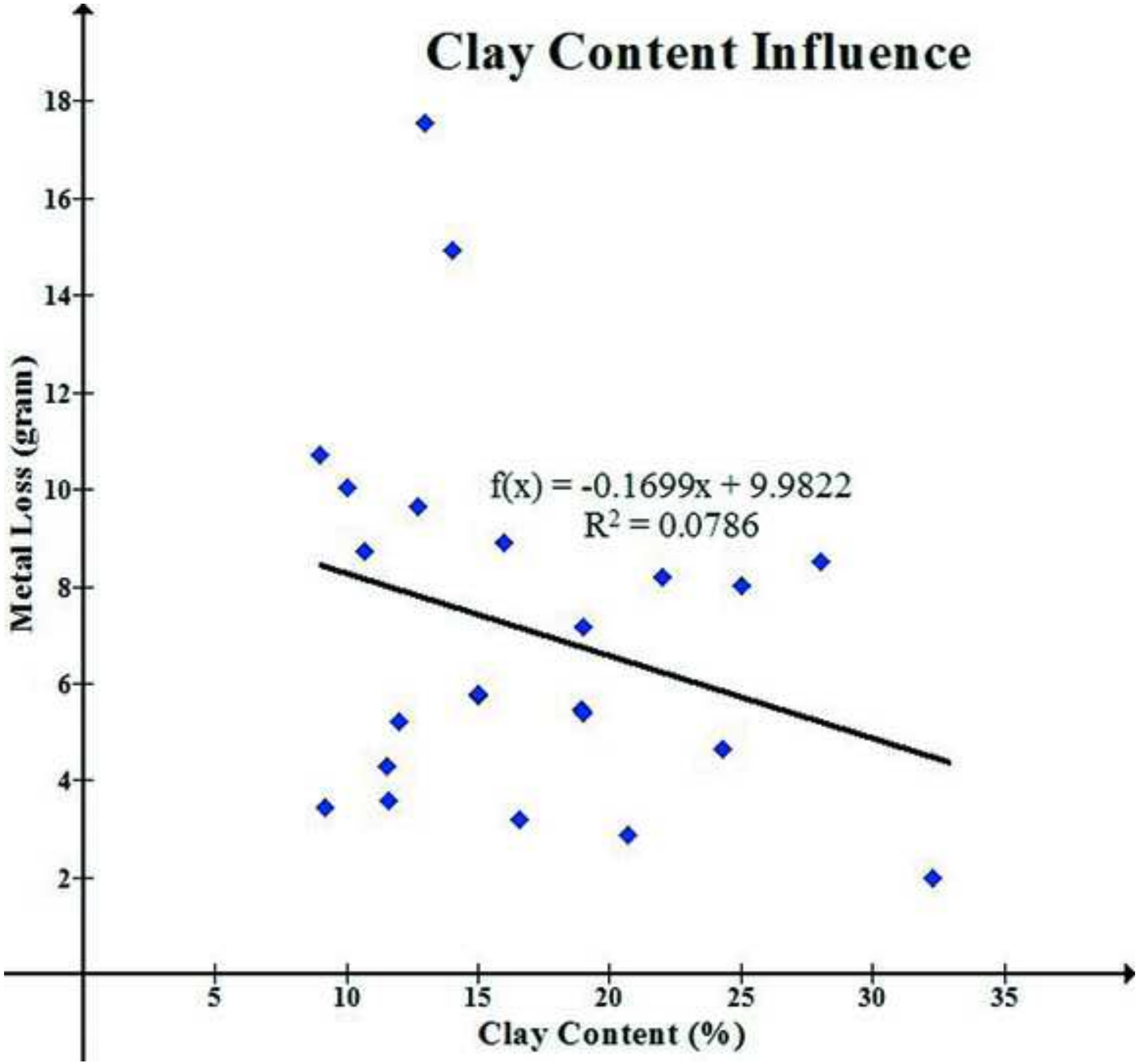

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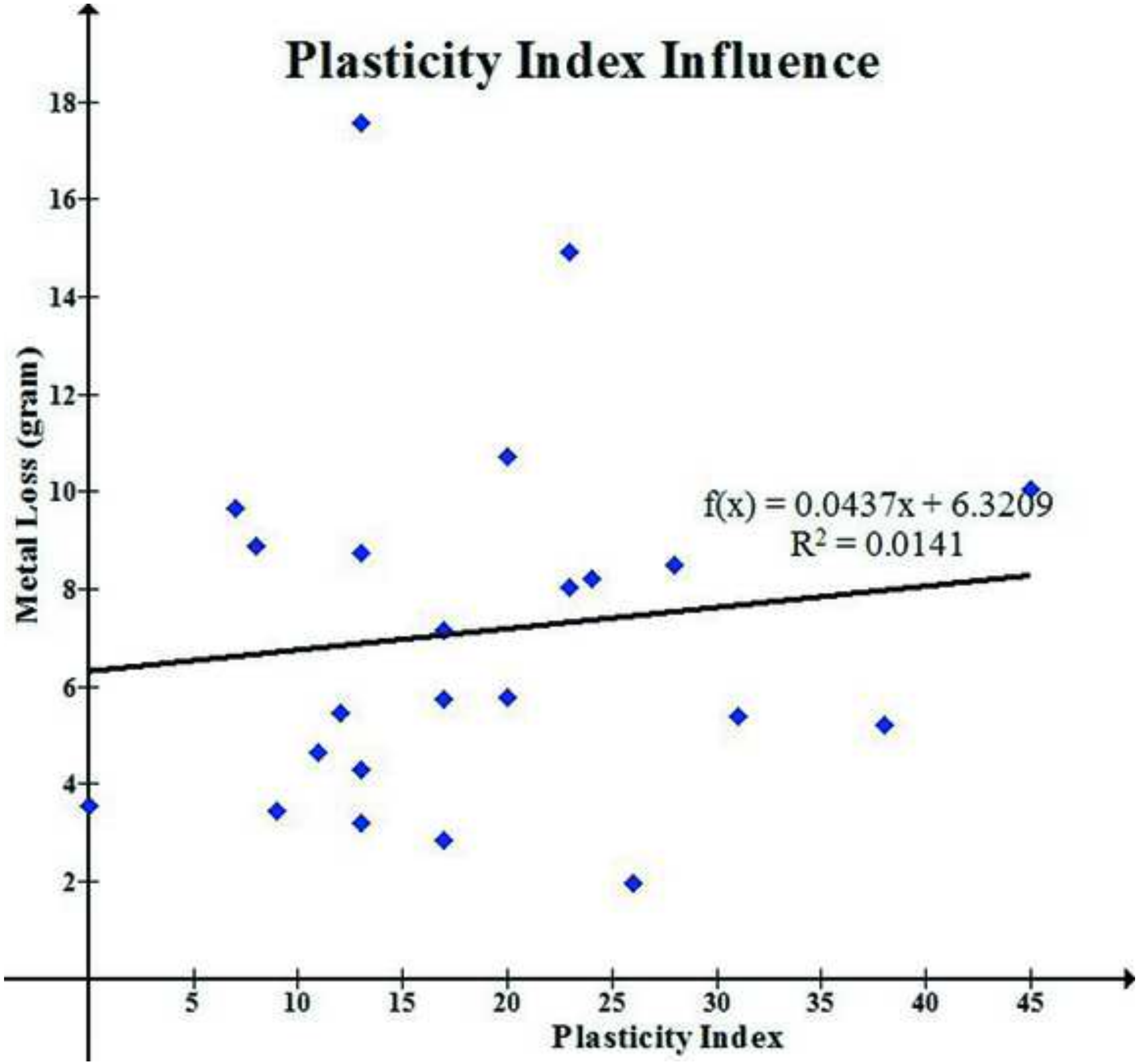

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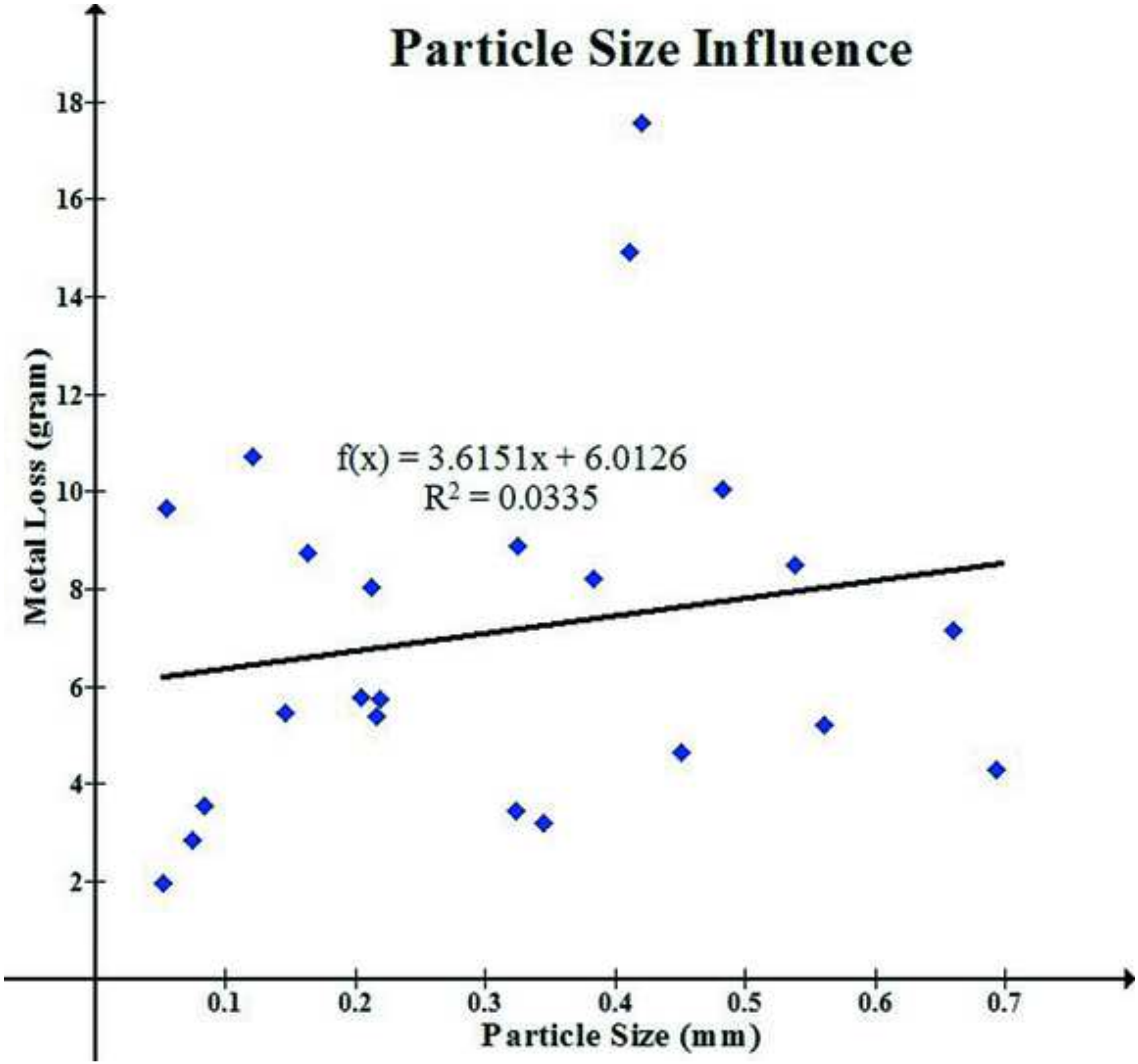

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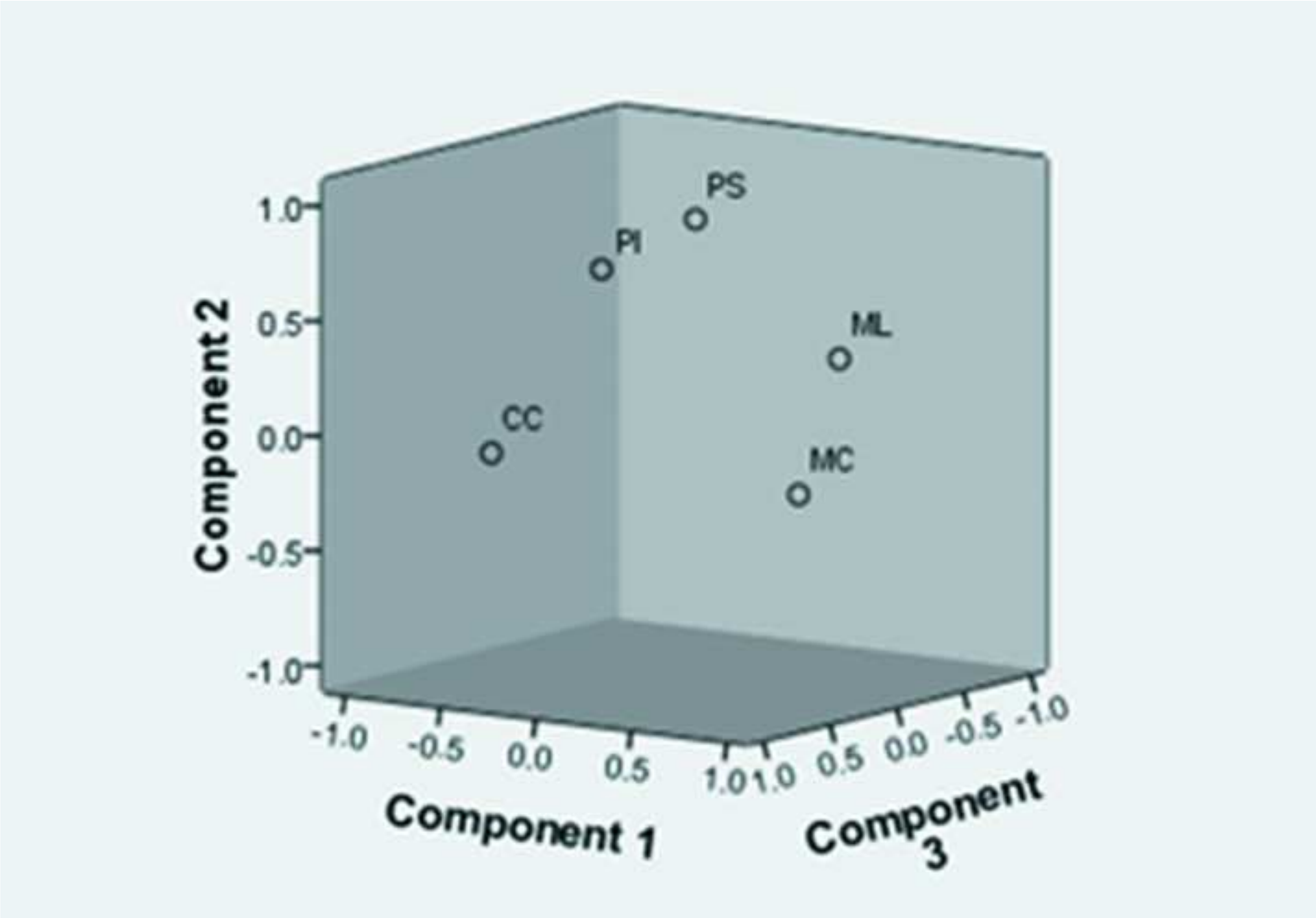

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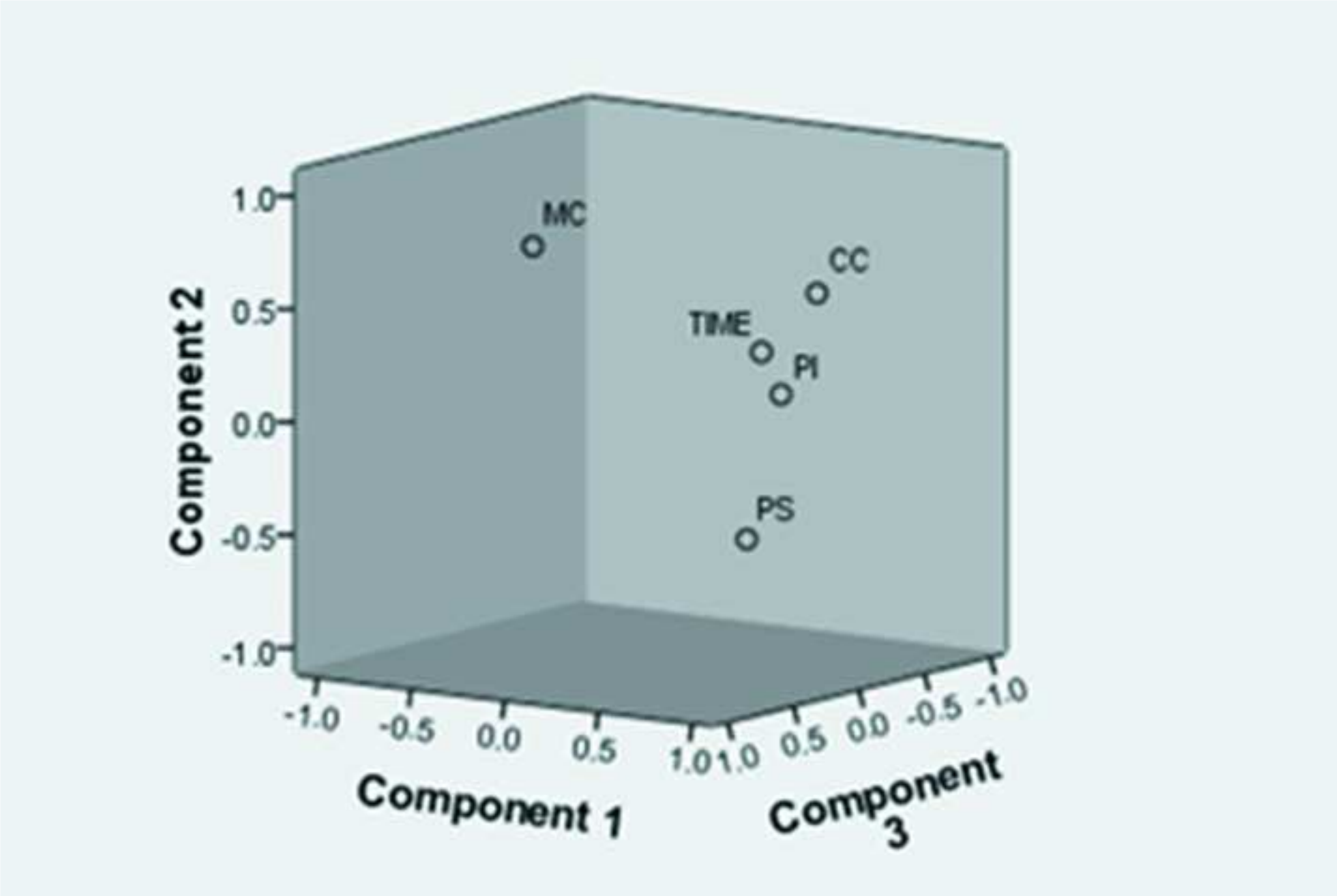

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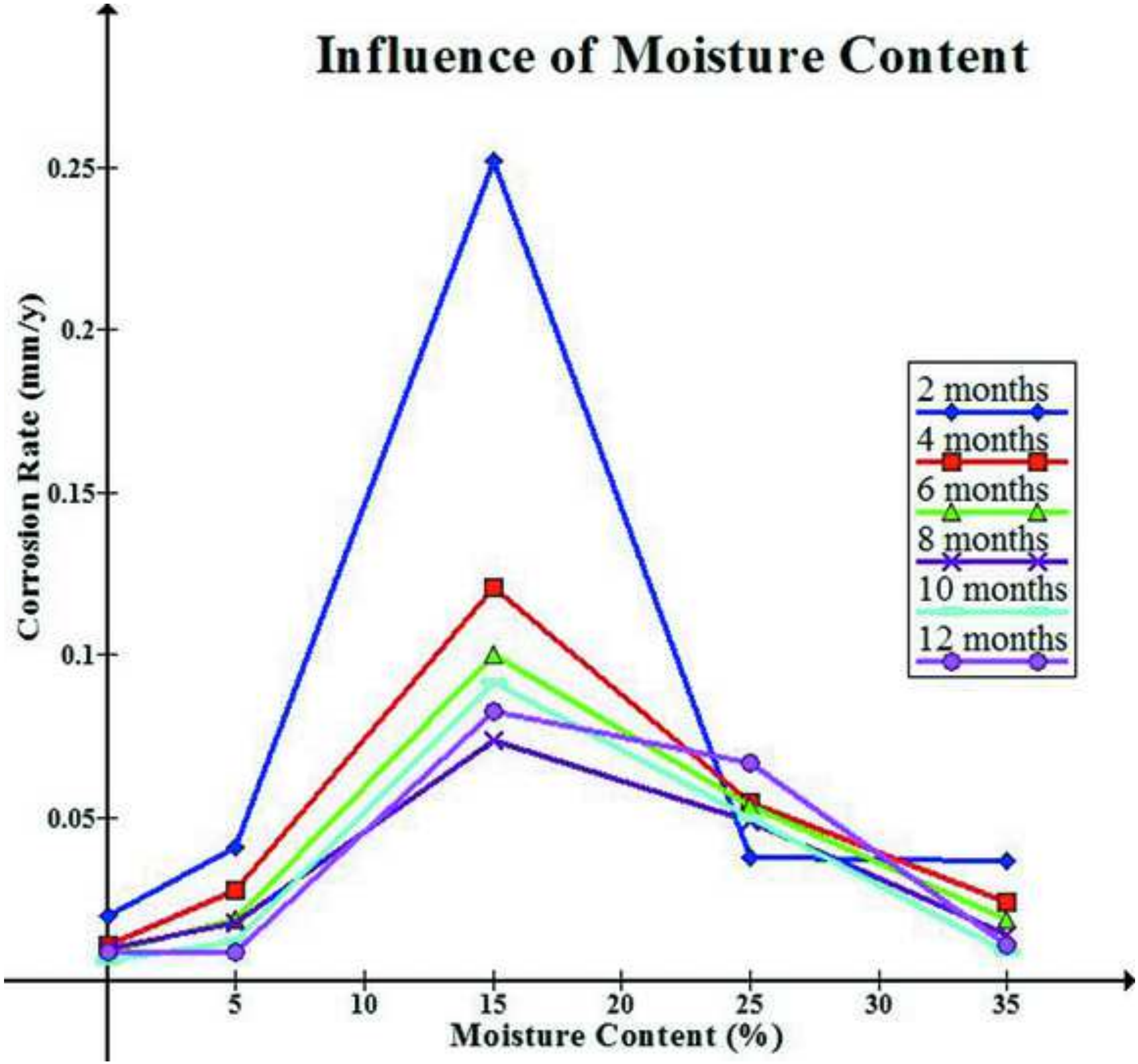

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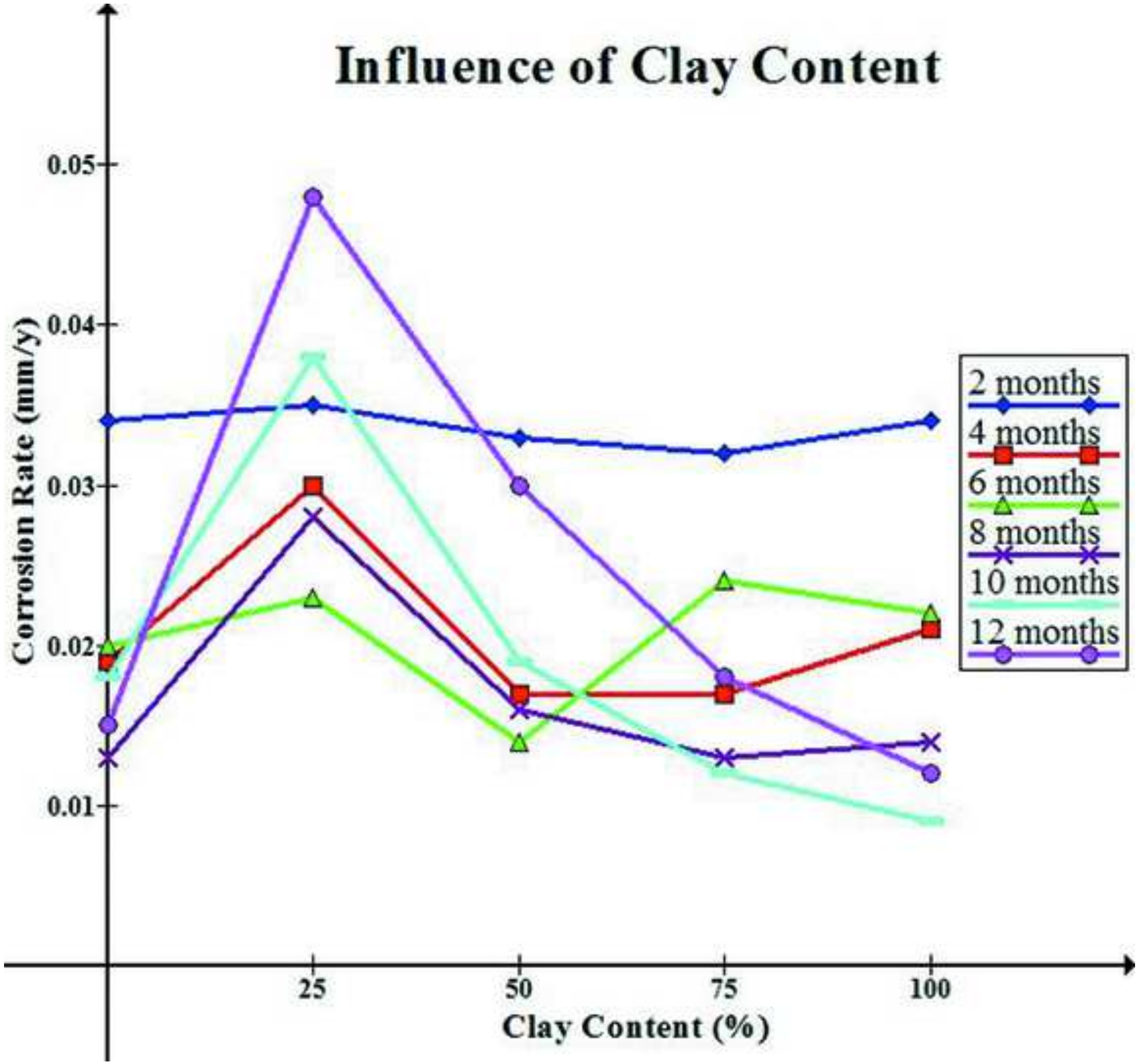

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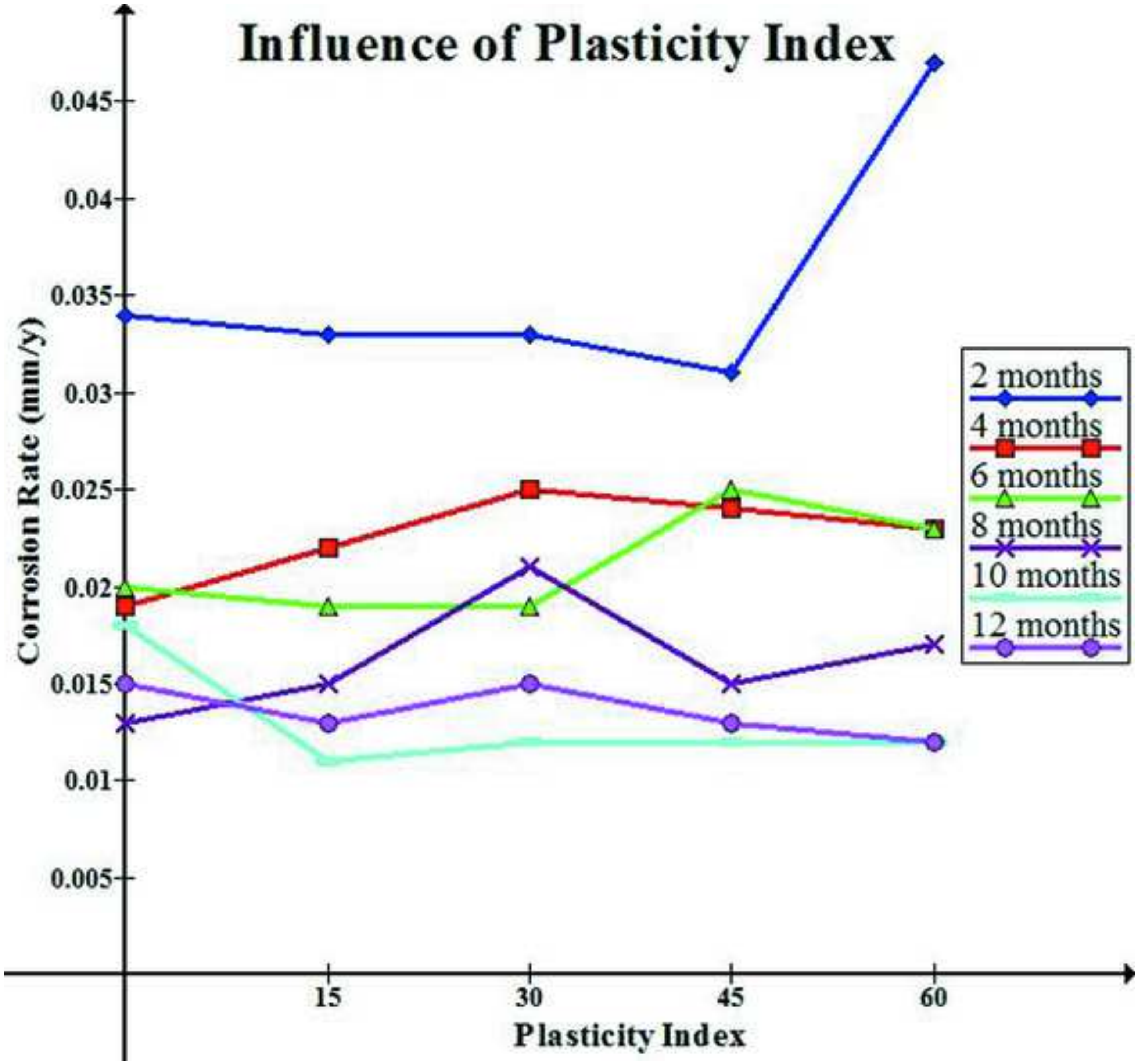

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