Development of prevention strategies for silica scaling based on neural network supervised machine learning

Saefudin Juhri[1], Kotaro Yonezu[1], Ryunosuke Terashi[1], Tadahiro Naritomi[1], Eiki Watanabe[2], Shogo Sato[2], Naho Inoue[2] and Takushi Yokoyama[2,3]

[1]Dept. Earth Resources Engineering, Faculty of Engineering, Kyushu University, Fukuoka, Japan
[2]Kyudensangyo, Co. Ltd., Fukuoka, Japan
[3]Dept. Chemistry, Faculty of Science, Kyushu University, Fukuoka, Japan

juhri@mine.kyushu-u.ac.jp

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ABSTRACT

Scaling is a persistent challenge in geothermal energy extraction, affecting the subsurface and surface facilities of geothermal power plants. However, a universal prevention method has not been established due to the complexity of scale formation and diverse types of scale deposition. Recently, artificial intelligence (AI) has been vastly used in various disciplines of science, including geothermal exploration and optimization of energy utilization. Our previous work attempted to utilize supervised machine learning (SML) to accurately predict the formation rate of silica scale in a geothermal environment. The produced models yielded error values of < 0.15, as root mean squared error (RMSE), suggesting the applicability of the models to predict silica scale formation.

In this study, we utilize the SML models to develop mitigation strategies against silica scaling. The strategies were developed based on the contribution factors of the chemical parameters of geothermal water. Then, three scenarios were evaluated: (1) pH modification only, (2) pH modification with removal of metals, and (3) pH modification and polymerization of oversaturated silicic acid. In addition to the modeling, onsite experiments of batch metal immersion were also conducted at the Hatchobaru geothermal power plants to examine the strategy and the development of a new silica scale inhibitor. The experiments were conducted at a temperature of ~90 °C, simulating the aging tank's condition. This study exhibits the potential of a machine-learning model to predict and assist in the mitigation of silica scale formation. With further and more experiments in more diverse properties of geothermal water, future models are expected to be applicable to more geothermal fields.

1. INTRODUCTION

Scaling is a persistent challenge in geothermal energy extraction, affecting the subsurface and surface facilities of geothermal power plants. However, a universal prevention method has not been established due to the complexity of scale formation and diverse types of scale deposition even within a single geothermal system (Juhri et al., 2023). Silica scale was found in almost all surface facilities such as production wells, separators, brine pipelines, reinjection wells, and even within the pores of reservoir rocks (Yanaze et al., 2019 and Juhri et al., 2023). In general, silica scale formation, driven by the degree of saturation of dissolved silica species, is controlled by factors such as, temperature of the geothermal water, salinity, pH, as well as metal and fluoride contents (Tarutani, 1989; Yokoyama et al., 1993; Manceau et al., 1995; and Gallup, 1997).

Recently, artificial intelligence (AI) has been vastly used in various disciplines of science, including geothermal exploration and optimization of energy utilization. Specifically, machine learning has been used to assist the characterization of geothermal reservoirs, particularly in determining geochemistry of reservoir fluid and temperature, improving classical solute geothermometry (Okoroafor, et al., 2022).

In our previous report, we exhibited the use of supervised machine learning (SML) to predict the formation rate of silica scale in geothermal environments (Figure 1) based on empirical data from onsite experiments (Juhri et al, 2024). The learning data was collected from more than 20 on-site experiments in five geothermal power plants, with a wide range of salinity, pH, and the concentrations of Si, Fe, and Al. The produced model yielded error values of < 0.15 as a relative root mean squared error (RRMSE) and R^2 value of > 0.99 (Figure 2), suggesting the high accuracy of the models to predict silica scale formation.

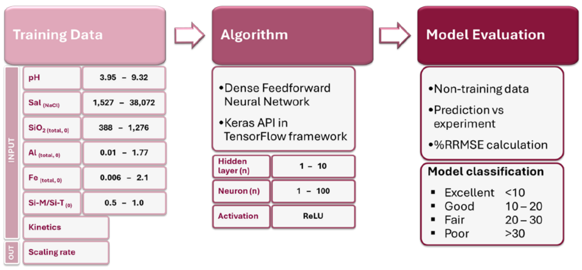

Figure 1: Workflow of the supervised machine learning for the prediction of silica scale formation rate based on chemical properties of geothermal water and kinetics of the polymerization and adsorption of silicic acid in geothermal water (Juhri et al., 2024).

Therefore, we attempted to use the machine learning model to evaluate inhibition scenarios in this study. The scenarios were built based on the contribution factor analysis from the machine learning model that quantify how each input parameter affects the formation rate of silica scale. Following the prediction result of each scenario, onsite experiments of metal plates immersion were conducted to examine the precipitation behavior of silica scale after the implementation of the inhibition scenarios.

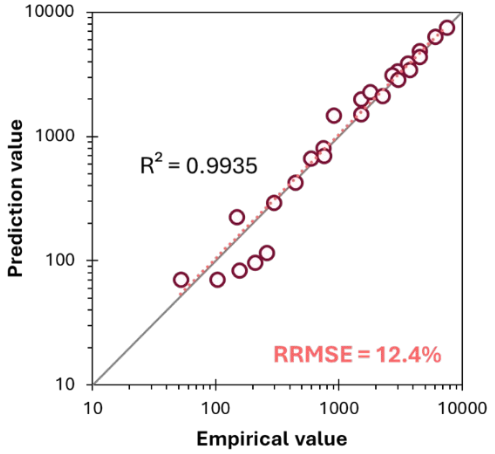

Figure 2: Result of model evaluation in predicting the rate of silica scale formation of a non-training data (Juhri et al., 2024).

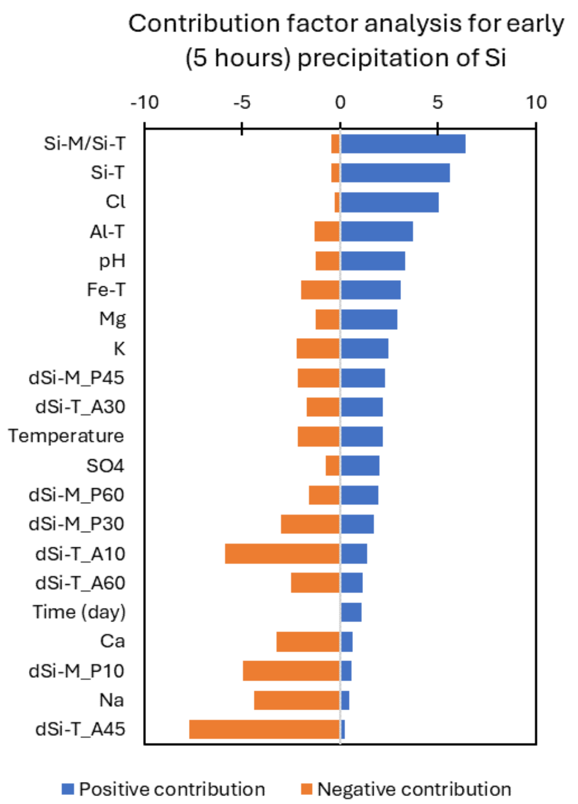

Figure 3: Contribution factor of input parameters (major characteristics of geothermal water and kinetics behavior of dissolved silicic acid) to the precipitation of Si on the metal plates within 5 hours of experimental (Juhri et al., 2024).

2. CONTRIBUTION FACTOR ANALYSIS AND INHIBITIONS STRATEGIES

The result of factor analysis using the ML model showed that the precipitation of silica on a metal surface was strongly controlled by the degree of silica polymerization, as well as total concentrations of Si, Cl, Al, pH, and Fe (Figure 3). Therefore, the inhibition strategy examined in this study focused on the limiting the contribution of monosilicic acid and metals (Al, Fe, and Mg) in geothermal water to the formation of silica scale. The inhibition strategies were represented by the addition of several inhibitors that chemically limit the activity of monosilicic acid and metals in geothermal water. The inhibitors used in this study are polyacrylic acid (PAA), 4,5-dihydroxy-1,3-benzenedisulfonic acid (Tiron), and Acumer™5000 (refer to as Acumer).

PAA has been known to have a strong interaction with cationic metals owing to its negative charge carboxylic site (Gebhardt & Fuerstenau, 1983; Lützenkirchen et al., 2011; Masunaga et al., 2014). Tiron is a derivative of catechol which effectively interacts with silicic acid through OH-edge sharing at near-neutral pH condition (Bai et al., 2011). In addition, Tiron has also been known to effectively chelate with Fe and Al (Nucera et al., 2023). Furthermore, Acumer is also known as scale inhibitor and dispersant for silica and magnesium silicate (Semiat et al., 2003). However, Gallup & Barcelon (2005) suggested that overdosing this type of inhibitor might lead to flocculation and precipitation. These three inhibitors were selected and evaluated for their diverse properties and inhibition mechanisms.

3. METHODS

The study was carried out in two stages: (1) prediction of silica scale formation rate in various scenarios and (2) on-site inhibition experiments to observe the precipitation behavior of silica scale after the implementation of the inhibition scenarios.

3.1 Machine Learning Workflow for the Prediction of Silica Scale Behavior

In stage 1, the machine learning model was used to predict the formation of silica scale based on several inhibition scenarios. The prediction of silica scale formation rate was performed using geothermal water from Hatchobaru geothermal power plant. The chemical properties of geothermal water are summarized in Table 1. As seen in Figure 4, the inhibition scenarios were selected according to the result of contribution factor analysis. In this study, the inhibition scenarios consist of:

a. pH modification only
b. pH modification and metals (Fe, Al, Mg) removal/deactivation
c. pH modification and silica polymerization
d. pH modification and silica removal

The machine learning model were then tasked to predict the formation rate of silica scale of each inhibition scenario. The result of the prediction was finally compared with the empirical result of batch experiment of metal plates immersion after the addition of inhibitors.

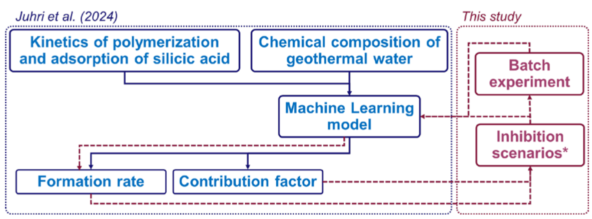

Figure 4: Workflow of the use of machine learning for the prediction of silica scale formation based on several inhibition scenarios.

Table 1: Chemical properties of the geothermal water for on-site inhibition experiments.

	Geothermal water
pH	8.5
EC (mS/m)	617
Na (mg/l)	1160
K (mg/l)	129
Ca (mg/l)	40
Mg (mg/l)	0.02
Al (mg/l)	0.38
Cl (mg/l)	1890
SO_4 (mg/l)	179
HCO_3 (mg/l)	24.0
Fe (mg/l)	0.02
$SiO_2(T_0)$ (mg/l)	486
$SiO_2(M_0)$ (mg/l)	486

3.2 Experimental Procedures for the Batch Experiments of Metal Plates Immersion

In stage 2, the inhibitors (PAA, Tiron, and Acumer) were evaluated for their inhibition efficiency through batch experiment of metal immersion. In this study, we used copper plate as a platform on which silica scale can grow. Five metal plates were suspended inside a 1L polypropylene bottle in which geothermal water was filled and mixed with the inhibitors (Figure 5). A plate was retrieved every one hour while the mixture of geothermal water and inhibitor was renewed. The dosage of PAA and Acumer were set to 10 ppm (as active site) to avoid flocculation, and Tiron was set to 600 ppm to achieve a 3:1 ratio against silicic acid in geothermal water.

Figure 5: Suspended metal plates in a 1L polypropylene bottle for batch experiment of silica scale inhibition.

All experiments in stage 2 were done parallelly on-site at Hatchobaru geothermal power plant, at a temperature of ~95 °C. This includes a control experiment using only geothermal water without addition of any inhibitor. The solution inside the reaction vessel was stirred at a constant speed of 120 rotation per minute or rpm.

After the on-site experiment, the metal plate samples were transported to the Laboratory of Economic Geology, Kyushu University for a for scanning electron microscope (SEM) observation to observe the particle precipitated on the surface of the copper plates. Furthermore, laser ablation inductively coupled plasma mass spectrometry (LA-ICP-MS) analysis was also conducted to determine the concentrations of Si, Fe, and Al on the surface of the copper plates.

4. RESULTS

4.1 Prediction of Scale Formation Rate

3.1.1 pH modification

The pH of geothermal water was modified from its original pH of 8.5 down to 5.0. Commonly, this is done by injection of a certain dosage of sulfuric acid into the geothermal water. In this scenario, the kinetics of polymerization and adsorption of geothermal water were subsequently affected, i.e., the rates of silicic acid's polymerization and its adsorption on silica surface were slowed down.

The prediction result is presented in Figure 6. The precipitation rate was rapidly decreased upon pH reduction to 8.0, then gradually decreased along with pH reduction. Compared to the non-modified scenario, pH reduction to 5.0 yielded 13% efficiency. If silica scale is assumed to grow linearly, this scenario might result in 15% increase in the system's life expectancy.

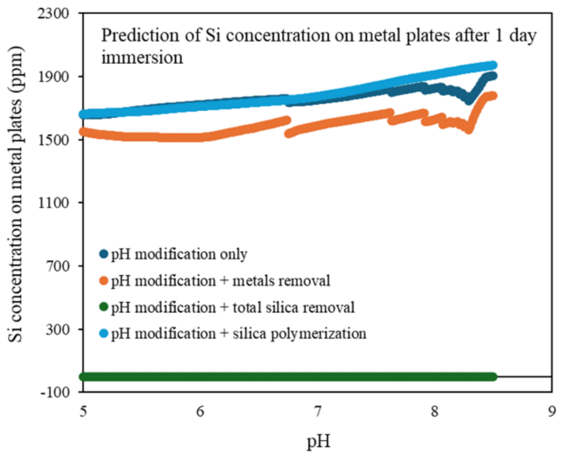

Figure 6: Prediction of Si precipitation rate on metal surface after 1 day immersion in geothermal water.

3.1.2 pH modification and metals removal/deactivation

In addition to pH modification, metals (Fe, Al, Mg) were removed or deactivated from geothermal water. In practical, this scenario can be achieved through adsorption of metals on a solid surface or chelation of them by chelating agent such as Tiron (Bai et al., 2011) and EDTA (Juhri et al., 2025). The inhibition behavior over the pH range resembled pH modification, however the effect of the removal of metals were more pronounced at around pH 6 (Figure 6). Furthermore, the model also shows that removal or deactivation of metals can improve the inhibition efficiency of silica scaling by 2× compared to pH modification only (Figure 7).

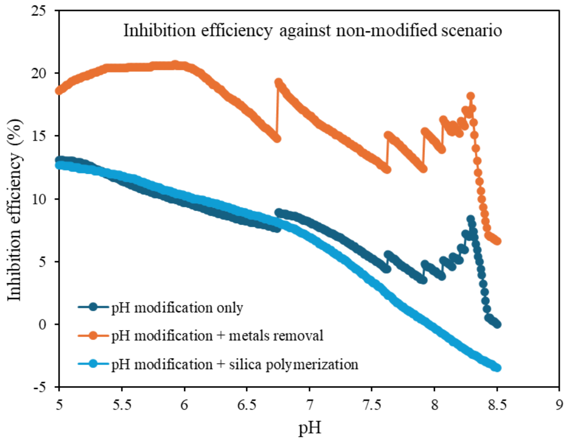

Figure 7: Inhibition efficiency of the three scenarios: pH modification only, pH modification with metals removal, and pH modification with Si full polymerization at 95 °C.

3.1.3 pH modification and silica polymerization

The oversaturated dissolved silicic acid was assumed to be fully polymerized into colloidal silica particle in this scenario. Consequently, the degree of polymerization (ratio of monosilicic acid concentration over total concentration of silicic acid) at initial condition was changed while the total concentration of silicic acid remained. Furthermore, this scenario also affected the kinetics of the polymerization and adsorption of silicic acid.

As seen in Figure 6, more silica was precipitated on the surface of metal plates at around the original pH of 8.5. Then, this strategy appears to give negligible effect compared to that of pH adjustment below 7.5.

3.1.4 pH modification and silica removal

In this ultimate scenario, silica is assumed to be completely removed from geothermal water, leading to the non-existence of silica scaling (Figure 6). In practical, this strategy can be achieved through several methods. However, most silica removal methods require pre-treatment procedure of the geothermal water to attain optimum recovery of silica.

4.1 Silica Scale Formation Rate on Metal Plates

3.2.1 SEM observation

SEM observation showed that silica particles were precipitated on the surface of copper plates after 5 hours immersion in geothermal water without any addition of inhibitors (Figure 8). In contrast, less silica particles were precipitated after the addition of Tiron and Acumer. On the other hand, more silica particles were precipitated after the addition of PAA. This shows that PAA caused the coagulation of silica in geothermal water and enhanced its precipitation. On the contrary, Tiron and Acumer seemed to effectively prevent silica precipitation.

3.2.2 LA-ICP-MS analysis

Results of LA-ICP-MS analysis agrees with the SEM observation. As seen from Figure 6, Si concentration increased to around 2000 ppm after 1 hour immersion without addition of any inhibitors. Then, the concentration continued increasing to around 8000 ppm after 5 hours of immersion. Furthermore, addition of PAA increased to 11000 ppm after 5 hours immersion. On the contrary, Si concentration remained very low after the addition of Acumer and Tiron. This result shows that Tiron gave the highest inhibition efficiency compared to Acumer and PAA, likely by actively attacked metals and silicic acid species in geothermal water.

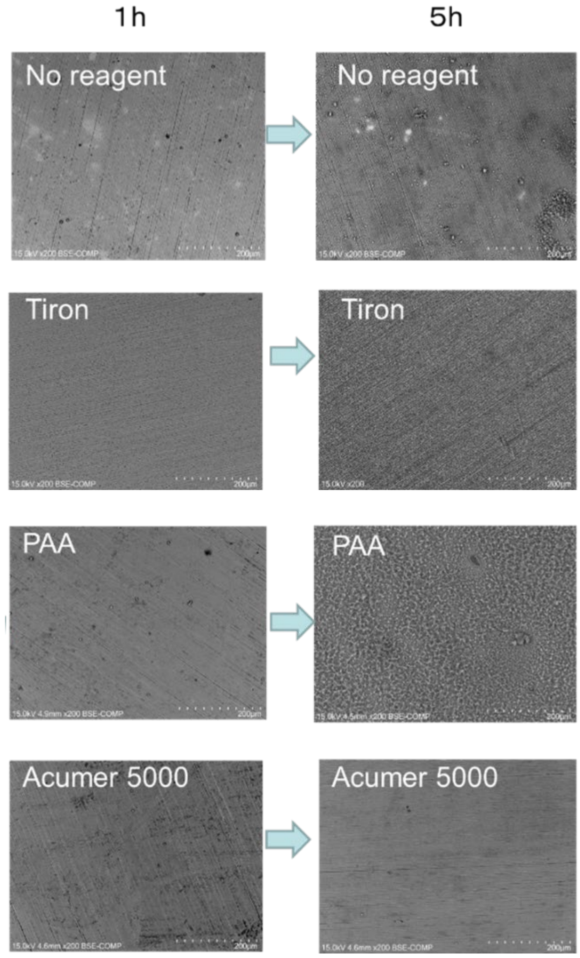

Figure 8: SEM observation of metals plates after 1- and 5-hours immersion in geothermal water without any treatment, with addition of Tiron, PAA, and Acumer.

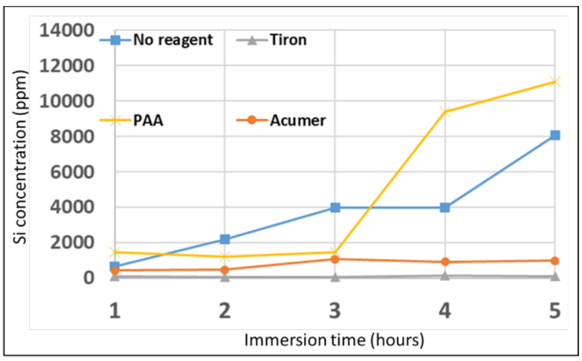

Figure 8: Concentration of Si from LA-ICP-MS analysis on the surface of metal plates over immersion time in geothermal water with and without addition of inhibitors.

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5. DISCUSSIONS

As mentioned earlier, PAA has been known to have a strong interaction with cationic metals owing to its negative charge carboxylic site (Gebhardt & Fuerstenau, 1983; Lützenkirchen et al., 2011; Masunaga et al., 2014). Therefore, the addition of PAA represents deactivation of metals in geothermal water. However, this method yielded the lowest inhibition efficiency (Figure 9). In fact, PAA increased the silica scaling rate. This is likely due to the presence of metals as oxides (e.g., $Fe(OH)_3$ and $Al(OH)_4^-$) after geothermal water flushing into atmospheric condition at near-neutral pH. The presence of neutral and negatively charged oxide metals reduced the efficiency of PAA to deactivate metals in geothermal water.

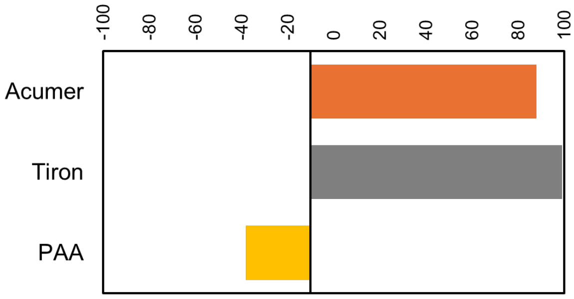

Figure 9: Inhibition efficiency after 5 hours of immersion experiment of addition of inhibitors.

Meanwhile, the addition of Acumer primarily reflects deactivation of dissolved silica in geothermal water as it is known as a dispersant for silica and magnesium silicate (Semiat et al., 2003). This method yielded 88% inhibition efficiency in the batch experiment. This result agrees with the SML model's prediction although higher than the prediction.

Finally, the addition of Tiron exhibits the effect of metals and silica deactivation. This is due to its effective interaction with silicic acid through OH-edge sharing at near-neutral pH condition (Bai et al., 2011) and its effective chelating behavior with Fe and Al (Nucera et al., 2023). This method was particularly more effective due to the presence of dissolved silica and metals as oxides ($Si(OH)_4$, $Fe(OH)_3$ and $Al(OH)_4^-$). This method yielded the highest inhibition efficiency (Figure 9), indicating the effectiveness of Tiron in deactivating metal hydroxides and dissolved silica and its advantage for the inhibition of silica scale.

The result of inhibition experiment using Tiron was in agreement with the prediction from the machine learning model that show that the deactivation of metals in geothermal water will result in a higher inhibition efficiency. However, the experimental result using PAA pointed out the importance of understanding the species of metals presence in geothermal water. Then, inhibition strategy should be developed in accordance with the detailed chemical properties of the geothermal water.

6. CONCLUSIONS

This study shows the applicability of machine learning model to construct a mitigation strategy for the prevention of silica scaling in geothermal field. The supervised machine learning model predicted that metals removal and silica removal will yield higher inhibition efficiency than pH modification only. This prediction was evaluated using on-site batch experiments of metal plates immersion with the addition of various inhibitors such as PAA, Acumer, and Tiron. The on-site experiment results agreed with the supervised machine learning model's prediction, where deactivation (comparable to removal) of metals and silica using Tiron yielded the highest inhibition efficiency. Furthermore, this study exhibited the effective use of a supervised machine learning model to develop inhibition strategy against silica scaling. Further, the model can be updated with more experiments and field test to increase its accuracy and expand its applicability.

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