RESEARCH ARTICLE

Predicting load on ground anchor using a metaheuristic optimized least squares support vector regression model: a Taiwan case study

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Abstract

Failure of ground anchor is a major cause of landslides and severe natural hazards, especially in the highly developed mountainous areas such as New Taipei City. Accurately estimating load on ground anchors is thus essential for evaluating the stability status of slope to prevent landslide from happening. This study first employed correlation analyses to identify possible influential factors of load on ground anchors. Second, various artificial intelligence models were used to map the relationship of the found influencing factors with the current load on ground anchors. The results indicated that the symbiotic organisms search-optimized least squares support vector regression (SOS-LSSVR) model had the optimal accuracy by earning the smallest value of mean absolute percentage error (9.10%) and the most outstanding value of correlation coefficient ($R = 0.988$). The study applied the established inference model for the real case of estimating load on un-monitoring ground anchors. The analyzed results strongly advised administrators to conduct site surveying and patrolling more frequently to take early proper actions. In summary, the obtained results have demonstrated SOS-LSSVR as an effective alternative for the conventional subjective evaluation methods, which is able to rapidly provide accurate values of load on un-monitoring ground anchors.

Keywords: load on ground anchor; slope stability; load cell; artificial intelligence; symbiotic organisms search (SOS); least squares support vector regression (LSSVR)

1. Introduction

A ground anchor is an efficient and economical structural element used to stabilize slopes and to prevent deformation of the external soil layers by transferring the slope forces to the inner stable rock layers via tendons. Ground anchors have been a preferable and broadly used structure for reinforcing slopes (Zhang & Wang, 2017; Qu, Luo, Hu, Jia, & Zhang, 2018; Xue et al., 2018), especially in Taiwan where most cities are located among high mountains; thus, the extension of transportation and in-frastucture usually leads to the construction of ground anchor systems. Remarkably, New Taipei City has nearly 88% of the total area occupied by hilly or mountainous terrain, indicating that the flat land available for developing the city is minimal (Council of Agriculture, 2018). Expanding urban space thus necessitates the installation of ground anchor systems to facilitate the construction of infrastructure. Therefore, hundreds of thousands of ground anchors have been installed across Taiwan to date.

Along with available ground anchors, newly constructing an enormous number of ground anchors entails massive works...
of inspection, monitoring, and maintenance. Despite great attempts to conduct regular inspection and maintenance, failures of such structures still occur and result in fatal disasters and long-term negative impacts on the region of happening. A landslide that occurred on 25 April 2000 at milestone 3.1 km of the Formosa freeway in Taiwan is a typical example of ineffectively using ground anchors that caused a severe landslide with 200,000 m² of soil sweeping through a highway below and killed four people. Hence, the Ministry of Transportation and Communication of the Taiwan government launched an extensive inspection and a comprehensive maintenance program for existing anchored slopes. More than 100,000 ground anchors have been inspected (Liao, 2018).

Because the anchor structures can be subjected to additional loads induced by either external or internal factors during their life cycle (Fujiiwara & Sakai, 2016), the long-term performance of ground anchors has continuously been questioned. A standard solution of the authorities in response to this problem is installing monitoring devices on the anchored slope to track the minute changes in the hill that can enable preemptive warnings regarding impending danger (Wang, Hwang, Luo, Jiang, & Xiao, 2013; Santos, Morais, & Carvalho, 2015). However, the budget allocated for purchasing, installation, and maintenance of such devices is limited; many ground anchors have been left un-monitored (Zhao, Kang, & Li, 2018). Furthermore, the majority of slopes are located in inconvenient places where electrical power is unavailable. Humans are exposed to the risks during the process of pulling lengthy cables and maintaining devices. Additionally, the tools are likely to be damaged due to lightning, rockfalls, and wildlife.

The load on ground anchors is also influenced by a variety of attributes, such as slope height, slope profile, the angle between slope aspect and dip direction, bedrock condition, block volumetric proportion, the thickness of vegetation cover, watershed area, the size of toe excavation, changes in slope gradient, groundwater level, etc., which may limit the determination of anchor safety status. Elicitating the relationships between load on anchors and each of its influencing factors is complex and potentially non-linear. Purely using human interpretation-based mathematical formulae is infeasible to map the underlying function of the load on anchors with its influencing factors. Essentially, the massive amount of valuable historical data collected by monitoring devices is usually un-utilized thoroughly as the mathematical formulae are established by a trial-and-error method; thus, this method may not cover a wide range of real-world working conditions of ground anchors.

Artificial intelligence (AI)-based inference models can be a viable alternative solution to the anchor load estimation problem. AI-based inference models simulate the human inference processes, inferring new facts from previously acquired information and changing adaptively in response to changes in the historical data (Gupta, Kumar, Sahoo, Sahu, & Sarangi, 2017; Kumar & Tripathi, 2019). AI-based inference models are thus a powerful data modeling tool capable of taking advantage of collected ground anchor data and generating complex input-output relationships of ground anchors. As per our best knowledge, the diversity of AI models for estimating the anchor load is still limited at conventional machine learning techniques such as least squares support vector regression (LSSVR) (Liu, Jiang, Han, & Zhou, 2019), back-propagation neural network (BPNN), and random forest (RF) (Pourghasemi & Rahmati, 2018). Therefore, there is still a large room for increasing the prediction accuracy of load on ground anchors.

In machine learning, hybrid models that incorporate mutual merits of different techniques have attracted increasing interest of researchers because of their robustness, efficiency, and superiority to baseline models. For instance, the LSSVR technique has been positively perceived by scholars in predicting load on ground anchors in terms of efficiency and computational time (Liu et al., 2019). However, the previous study simply applied the LSSVR with a trial-and-error method for setting hyper-parameter values of the model to seek a good generalization. Nevertheless, determining the ultimate performance of a prediction model is regarded as a complex optimization problem that may not be efficiently addressed by manual trials because the potential hyper-parameter values of the LSSVR model lie in large searching ranges.

Fusing symbiotic organisms search (SOS) (Cheng & Prayogo, 2014), a metaheuristic optimizer with the LSSVR technique (Suykens, Van Gestel, De Brabanter, De Moor, & Vandewalle, 2002) may be a promising solution to boost the prediction accuracy of anchor load and increase the automation of the prediction model. The superiority of the SOS algorithm over the widely used genetic algorithms (GA), particle swarm optimization (PSO), differential evolution (DE), and artificial colony (ABC) in solving engineering problems has been endorsed in various studies (Tejani, Savsani, & Patel, 2016; Tran, Luong-Duc, Duong, Le, & Pham, 2018). SOS is thus a promising tool to lift the performance of LSSVR to a higher level.

This study aims at developing and validating the efficiency of a hybrid AI model, named symbiotic organisms search-optimized least squares support vector regression (SOS-LSSVR), in predicting load on ground anchors. The SOS-LSSVR model is constructed by integrating the training process of LSSVR in the SOS algorithm in which SOS performs the optimization loop to determine the most appropriate hyper-parameters of LSSVR for obtaining the ultimate generalization. Meanwhile, the LSSVR technique used SOS-produced hyper-parameter values to build inference models of loads on ground anchors for evaluation. The values predicted by SOS-LSSVR is then used to assess the safety status of the slopes where un-monitored ground anchors are installed. Hence, the responsible authorities can rely on the reliable information to give an early solution for practical disaster prevention and management. This study expects to contribute in promoting the United Nations Goals for Sustainability, particularly the Goal of Sustainable Cities and Communities (Parnell, 2016).

The remainder of this paper is organized as follows: the second section presents methodologies and the proposed model for predicting load on ground anchor; the third section describes the data collection and processing; the fourth quarter shows the experimental results and evaluates the performance of the proposed model; the fifth is to analyze predicted results and give instructions for monitoring safety of ground anchors with discussion in details; and the last gives conclusions and suggestions of the study.

2. Methodology

2.1 Artificial intelligence models for anchor rock

In addition to conventional monitoring methods, some studies have begun to establish inference models for landslide prediction (Peng, Li, Li, Jiang, & Zhang, 2014; Tordesillas, Zhou, & Batterham, 2018). Tordesillas et al. (2018) indicated that landslide prediction requires systematic approaches and advanced algorithms in dealing with the variety, volume, and precision
of monitoring data. Peng et al. (2014) emphasized that multiple sources of slope monitoring information should be considered for landslide prediction. They used a Bayesian network to evaluate the failure probability of slopes. Li, Zhang, and Zhang (2018) propose an efficient Bayesian system to assess the slope safety using large-quantity field monitoring information. Lian et al. (2018) applied random vector functional link networks to estimate the slope displacement.

Recently, researchers have used artificial intelligence (AI) as a reliable tool to compensate for the numerous shortcomings in the conventional construction management and achieve more holistic assessments. The AI-based inference model is capable of simulating human decision-making behaviors of undertaking complicated and uncertainty-prone problems in construction management. By learning from historical case studies, artificial intelligence can deduce the decision-making and reasoning processes of experts. Artificial intelligence can assist decision makers in making appropriate decisions and preventing biases based on subjective opinions. The superiority of artificial intelligence algorithms has been demonstrated in various civil engineering-related problems, including slope stability analysis (Zhou et al., 2018; Lin, Wei, & Junjie, 2019; Pei, Zhang, Borana, Zhao, & Yin, 2019).

Radial basis function neural network (RBFNN) and support vector regression (SVR) are suitable for the slope monitoring system (Haonan & Hanqi, 2010; Kang & Li, 2016; Panahi, Gayen, Pourghasemi, Rezaie, & Lee, 2020). Liu et al. (2019) successfully put forward the least squares support vector machine to establish prediction model and estimate slope displacement. Pourghasemi and Rahmati (2018) compared the performances of landslide prediction among 10 artificial intelligence algorithms (e.g. ANN, SVM, random forest, regression trees, and naive Bayes), and the random forest algorithm exhibited the best accuracy.

The previous studies mainly concentrated on directly forecasting occurrence of landslides, but the load on ground anchors. It is worth noting that the ground anchor system is a significant structure for preventing the displacement of soil and rock. Therefore, the current load on ground anchors needs to be accurately calculated to provide reliable information for rapidly giving solutions to avoid occurrence of a landslide. It is critical to develop a novel inference model capable of fast and accurately predicting load on ground anchors to track/monitor the safety of slopes reinforced by ground anchors.

### 2.2 Symbiotic organisms search-optimized least squares support vector regression

The SOS-LSSVR model is a hybridization of SOS and the LSSVR technique. Thus, it contains the reciprocal merits of both LSSVR and SOS that enable the model to automatically and efficiently solve problems involved uncertain or partially unknown processes or issues with complexity and high dimension. The non-linear relationships between the input and output variables can be captured accurately after terminating the parameter optimization process of SOS. Detailly, the function of LSSVR, is to determine the relationship between input variables and an output variable and then provide prediction values to calculate objective functions of SOS. Meanwhile, the SOS engine carries out the optimization process to improve the suitability of the optimal parameters $\gamma$ and $\sigma$ for LSSVR at each iteration ($\gamma$ represents a normalized variable, and $\sigma$ represents a kernel function parameter). Accordingly, the forecast accuracy of LSSVR increases for each iteration of the optimization process.

It is worth noting that the learning process of SOS-LSSVR entirely relies on historical data without the need for manual intervention, as shown in Fig. 1.

(i) Training data

Training data are used for establishing the estimation model of load on the anchor. In this model, all input and output parameters are normalized into a range of [0, 1] to avoid the bias of greater numeric fields (Hsu, Chang, & Lin, 2003).

(ii) LSSVR construction

This process will construct many potential prediction models using parameter values ($\gamma$ and $\sigma$) provided by SOS and the training dataset from the previous step. The prediction models then yield estimated values of load on ground anchors. Hence, each model produces different load estimation values for the accuracy comparison in the next step.

(iii) SOS parameter search

SOS is used to test potential combinations of both parameters and improve the setting after every searching loop. The searching process is implemented through phases—mutualism, commensalism, and parasitism. The fitness value of each solution will gradually be improved. The Fig. 2 below presents the pseudo-code of the SOS algorithm.

(iv) Fitness check

This process will compare the error of prediction values to select and save the best model for each iteration. In this study, root-mean-square error (RMSE) is used to represent model accuracy in the objective function, as shown in the below equation. The training data is divided into two sets: the first set includes 80% of data for constructing a prediction model and the second set comprises the rest for validating the prediction model and makes sure the prediction model overcomes the overfitting problems (Bishop, 2006).

$$Fitness \ value = \frac{RMSE_{val} + RMSE_{train}}{2}.$$ 

where $RMSE_{val}$ and $RMSE_{train}$ indicate the value of root-mean-square error for validation data and training data, respectively.

(v) Termination criteria

Once the termination condition is met, the optimization process will stop. In this study, the total number of SOS iterations was used as a termination criterion.

(vi) Optimal LSSVR model and parameters

The optimal parameter values are found when the optimization process terminates, meaning that LSSVR can use those values to accurately map the relationship of influencing factors and load on ground anchors.

(vii) LSSVR testing

The constructed prediction model is then utilized to measure the load on the anchor rock of the testing dataset. This study used a 10-fold cross-validation method for evaluating the models’ performance to avoid bias in dividing training and testing data. Hence, there will be 10 pairs of parameter values corresponding to each testing fold.

### 3. Data Collection and Processing

#### 3.1 Factors affecting load on ground anchor

To identify the possible influential factors that may cause a landslide, the characteristics and functions of ground anchors must be addressed. In general, a ground anchor can be driven...
deep into the earth, through a latent slide in the depth of a slope, and embed itself in a steady stratum or rock bed, which is then pulled to create sufficient frictional force (from the shear strength of the stratum or rock bed) on the sandwiched latent slide and to stabilize it (Miyata, Bathurst, & Konami, 2009; Fujiwara & Sakai, 2016).

The anchored type retaining wall, a typical structure in reinforced slope (Chen et al., 2016; Fujiwara & Sakai, 2016; Siemens, Bathurst, & Miyata, 2018), is the technique that relies on the high frictional force from the ground anchor to stabilize the slope and the retaining wall, thus preventing the disturbing slope (by excavation or refill) from sliding. The function of a ground anchor load cell is twofold: it measures the load exercised on the retaining wall or the ground anchor in the slope, and by doing so, helps monitor the changes in such loads (Fig. 3). Therefore, factors that affect the stability of a slope can also be the factors that cause a shift in ground anchor loads (Miyata et al., 2009; Fujiwara & Sakai, 2016). Consequently, the load monitoring of anchors is crucial for slope safety and long-term structure (Islam & Bogdan, 2018; Kwon, Seo, Choi, Jeon, & Kwon, 2018). Choi, Lee, Kim, and Park (2013) also indicated that the load cell, which measures the residual force of the ground anchor, is mainly utilized considering its great convenience in the installment and management in practice.

A wide variety of factors influence the fluctuation of the residual force of anchors and can further induce a slope to slide (Choi et al., 2013). Once the influential factors are well recognized, the estimation and prediction results of slope stability are more comfortable, reliable, and promising (Peng et al., 2014; Liu et al., 2019). The influencing factors can be categorized into biological factors and human elements. Biological elements are intrinsic conditions that already exist in slope, or extrinsic destabilizing conditions that have damaged the hill, such as topographic or geologic factors, vegetation, precipitation, and earthquakes. By contrast, human elements are mostly changed due to the construction of road and infrastructure, such as the height of toe-excavation or change in slope inclination. Correct selection of influential factors to estimate the load on ground anchor is thus not an easy task. In the literature, numerous studies have been conducted to analyze and determine those factors.

Uhlemann et al. (2016) indicated that precipitation is the triggering mechanism for the landslide. Besides, the monitoring of kinematic, hydrological, and climatic parameters plays a significant role in supporting the development of slope stability models. Dai, Lee, and Ngai (2002) stated that slope characteristics (e.g. slope aspect, slope inclination, slope height, and slope profile), mechanisms of failure and modes of debris movement, downhill path, and residual strength behavior of sheared zones were crucial factors of the landslide. Xue et al. (2018) also regarded the excavation and the presence of dip weak layers as the main contributory factors of slope failure. Peng et al. (2014) summarized that friction angle, cohesion, displacement, stress, pore

![Figure 1: Learning process of SOS-LSSVR.](https://academic.oup.com/jcde/advance-article/doi/10.1093/jcde/qwaa077/6035282)
water pressure, slope geometry, soil thickness, and drainage were essential indicators for slope safety evaluation. Seepage has also been identified as a critical factor strongly influencing slope stability status (Yan et al., 2015).

3.2 Data collection and processing

The construction works for the Wu Chong Creek section of the Huanhe Expressway was completed and opened to traffic in...
Optimized LSSVR for predicting load on ground anchors

Figure 3: Rock anchor components.

Table 1: Functions of the monitoring devices.

| Monitored targets | Device                | Condition measured                                      |
|-------------------|-----------------------|---------------------------------------------------------|
| Displacement      | Underground displacements | Slope inclinometer                                    |
| Hydrology         | Groundwater level     | Water level observation well                           |
| Retaining wall    | Deformation and tilting | Tiltmeters                                              |
|                   | Ground anchor load    | Ground anchor load cell                                 |
|                   |                       | Depths and displacements of sliding earth strata       |
|                   |                       | Changes in groundwater level                           |
|                   |                       | Rainfall within the region                             |
|                   |                       | Tilting of retaining walls                            |
|                   |                       | Changes in ground anchor load                         |

2011. This road section is 4.5 km long and runs through the hilly terrain with dip slopes (see Fig. 5). To ensure the stability of the artificial slopes along the Wu Chong Creek section and remain informed of their conditions, various survey and monitoring tasks have been conducted, including topographic surveys, geologic drilling, resistivity image profiling, natural gamma-ray logging, ground anchor monitoring, and the installation of other monitoring devices. In detail, many monitoring devices were installed at those monitoring sections, including slope inclinometers, water level observation wells, retaining wall tiltmeters, and ground anchor load cells, for the biological monitoring and measuring of artificial slopes. The functions of the devices are listed in Table 1.

Table 2 and Fig. 4 exhibit the devices deployed at each monitoring section. The survey and monitoring results gather information on topology, rock bed attitude, retaining wall locations, and dip slope characteristics. Based on the products and the purpose of this study, the data (ground anchor load cells, water level observation wells, tiltmeters, and slope inclinometers) from monitoring section 2-1 of the second tender (C1 and C2), 3-1 to 3-6 of the third tender (C3–C10), and 6-1 and 6-2 of the sixth tender (C11 and C12). Twelve monitoring sections were extracted for analysis of this study while the other six monitoring sections were excluded owing to incomplete data. The installation location of the twelve monitors are shown in Fig. 6.

It is worth noting that the investigated site involved cataclinal dip slopes that were stabilized with sheet pile retaining walls and prestressed steel-tendon ground anchors. Readers can refer to Table 3 for detailed geological information of the study field. Two thousand one hundred seventy-two batches of data were collected, in which 832 anchor loads closely reached the attention threshold of 55T, and the remaining 1340 are below the threshold value. The dataset is daily recorded at the maximum amount shown in the monitors from 1 January 2014 to 30 June 2014. Besides, the other five influencing parameters are also recorded for analyzing the impact on anchor loads.

This study adopted slope-sliding factors gleaned from literature as the possible factors affecting the ground anchor load. Additionally, because this study aimed to infer the ground anchor loads from artificial slopes, five parameters monitored by the monitoring devices were also considered as influential factors. Finally, a total of 20 potential factors were chosen for further validation.

A non-positive correlation between the input and output values would compromise the training and forecasting of the inference model and lead to excessive errors. This study implemented the correlation coefficient method to select significantly
Figure 5: Location of the Huanhe Highway on Terrain Map.

Table 2: Deployment of monitoring devices.

| Tender | Monitoring section | Slope inclinometer | Water level observation well | Tilt meter | Ground anchor load cell |
|--------|--------------------|---------------------|-------------------------------|-----------|-------------------------|
|        | Code               | Code | Depth (m) | Code | Depth (m) | Code | Code |
| 2nd    | 2-1                | S(A)-1 | 25     | W(A)-1 | 16     | WT(A)-1 | C-1 |
| 3rd    | 3-1                | S-1   | 25     | W-1   | 20     | WT(A)-3 | C-3 |
|        | 3-2                | S(A)-2 | 35     | W(A)-2 | 30     | WT(A)-4 | C-4 |
|        | 3-3                | S-2   | 25     | W-2   | 16     | WT(A)-5 | C-5 |
|        | 3-4                | S(A)-3 | 25     | W(A)-3 | 16     | WT(A)-6 | C-6 |
|        | 3-5                | S-3   | 30     | W-3   | 20     | WT(A)-7 | C-7 |
|        | 3-6                | S(A)-4 | 35     | W(A)-4 | 30     | WT(A)-8 | C-8 |
|        | 3-7                | S-2   | 25     | W-2   | 16     | WT(A)-9 | C-9 |
|        | 3-8                | S(A)-3 | 25     | W(A)-3 | 16     | WT(A)-10 | C-10 |
|        | 3-9                | S-3   | 30     | W-3   | 20     | WT(A)-11 | C-11 |
|        | 3-10               | S(A)-4 | 35     | W(A)-4 | 30     | WT(A)-12 | C-12 |
| 6th    | 6-1                | S(A)-5 | 30     | W(A)-5 | 16     | WT(A)-13 | C-13 |
|        | 6-2                | S-4   | 30     | W-4   | 16     | WT(A)-14 | C-14 |
|        | 6-3                | S(A)-6 | 30     | W(A)-6 | 16     | WT(A)-15 | C-15 |
|        | 6-4                | S(A)-7 | 30     | W(A)-7 | 16     | WT(A)-16 | C-16 |
|        | 6-5                | S-2   | 25     | W-2   | 16     |
| Total  | 16                 | 15     | 15     | 15     | 13     |

correlated parameters as the factors for constructing a prediction model of the load on ground anchors. The correlations are performed based on three efficient approaches, including Pearson’s correlation coefficient, Kendall’s tau-b, and Spearman’s rho and performed on SPSS 22.0 software (Corporation, 2013). Table 4 shows the final analysis results for 20 potential influencing factors in 2172 batches of data, which can be used as the basis for selecting factors affecting ground anchor load.

In this study, the factors that exhibited significant correlations in all three analyses (Pearson’s correlation coefficient, Kendall’s tau-b, and Spearman’s rho) were selected as the influential factors for the ground anchor loads in artificial slopes. Twelve elements were thus selected (Table 5) as input factors for the inference model of anchor load. Table 6 gives an illustration of sample data.

4. Experiment Results and Models’ Performance Comparison

To better assess the SOS-LSSVR model, the study compared its performance with those of other baseline AI models. The comparative models include linear regression (LR), SVR, BPNN, RBFNN, LSSVR (Chang & Lin, 2011), and evolutionary least squares support machine inference model. All models were run on Windows 10 and MATLAB 2010. Notably, a 10-fold cross-
validation method is also applied for those comparative models compared with the SOS-LSSVR model to mitigate the bias. The parameter values of those baseline models are shown in Table 7.

This study utilized four performance evaluation criteria for overall assessing the accuracy of prediction values versus actual values of load on ground anchor, including mean absolute percentage error (MAPE), mean absolute error (MAE), RMSE, and correlation coefficient (R), which were introduced to appraise the accuracy of the models. Formulas of these performance evaluation criteria are presented in Table 8.

As shown in Table 9 and Fig. 7, SOS-LSSVR achieved the incredible values for all four evaluation criteria. SOS-LSSVR earned 9.10% of MAPE for the testing phase, which is roughly 5% below the second-best model (RBFNN) and 21% below MAPE of ESIM. These obtained figures indicate that the SOS-LSSVR-captured function is closer to the underlying part of the load on ground anchors. The results also reveal that SOS can enhance the performance of LSSVR by 33.5% in terms of reducing the MAPE value, indicating that the combination of SOS and LSSVR is suitable and reasonable.

In addition to yielding the smallest values of MAPE, the developed model also attained the lowest amounts of RMSE (0.243 and 0.448) and MAE (0.170 and 0.217) for both the training and testing phases. As seen in Table 9, the overfitting problem of the SOS parameter searching is addressed thoroughly since the performance evaluation criteria of testing are slightly higher
Table 3: Strata types in the study area (provided by The Central Geological Survey, MOEA).

| Series | Strata                  | Code | Characters of soils/rocks                                                                 |
|--------|-------------------------|------|-----------------------------------------------------------------------------------------|
| Holocene | Alluvial layer          | a    | Gravel, sand, clay                                                                       |
|         | Terrace accumulation layer | t    | Gravel, sand, clay                                                                       |
| Pleistocene | Lava flows             | ahp  | Andesite and basalt                                                                      |
|         | Tuff breccia            | tb   | Andesite tuff breccia                                                                    |
| Miocene | Kueichulin formation   | Kc   | Massive or thick-bedded muddy sandstone, coarse-grained white sandstone, shale            |
|         | Nanchang formation      | Nc   | White sandstone, shale thin interbed coal-bearing seam                                   |
|         | Nankang formation       | Nk   | Thick gray calcareous sandstone, shale and sandstone, shales                             |
|         | Shihti formation        | St   | White sand and sandstone, shales, coal seams containing                                 |
|         | Taliao formation        | T1   | Upper to central sandstone, interbedded sandstone and shale lower part, the body part containing tuff |
|         | Mushan formation        | Ms   | white sandstone, black shale, and light interbeds of sand and shale, coal-bearing seams |
| Oligocene | Wuchihshan formation | Wc   | Upper Black shales, middle, and lower white coarse sand or gravel and sand shales         |
|         | Tatungshan formation   | Tt   | Gray-black hard shale, occasionally intercalated thin to thick argillaceous siltstone and thin fine-grained sandstone intercalated with convex lens body of tuff |
|         | Tsuku formation         | Tk   | Gray thin to thick siltstone interbedded with dark gray hard shale interbedded with light fine-grained sandstone |
|         | Kanko(u) formation      | Kk   | Gray hard shale with thin to thick argillaceous siltstone and fine-grained sandstone     |
|         | Szeleng sandstone       | S1   | Thick white lump to the folder shale too coarse quartzite                                |

Table 4: Results of the correlation analyses.

| Factors                                      | Pearson’s correlation coefficient | Kendall’s tau-b | Spearman’s rho |
|----------------------------------------------|-----------------------------------|-----------------|----------------|
| Slope aspect (◦)                             | ⊙                                 | ⊙               | ⊙              |
| Slope inclination (◦)                        | ⊙                                 | ⊙               | ⊙              |
| Slope height (m)                             | ⊙                                 | ⊙               | ⊙              |
| Slope profile                                | ⊙                                 | ⊙               | ⊙              |
| Stratum type                                 | ⊙                                 | ⊙               | ⊙              |
| The angle between slope aspect and dip direction (◦) | ⊙                                 | ⊙               | ⊙              |
| The angle between slope aspect and dip angle (◦) | ⊙                                 | ⊙               | ⊙              |
| Bedrock condition (%)                        | ⊙                                 | ⊙               | ⊙              |
| The thickness of weathered rock blocks (m)   | ⊙                                 | ⊙               | ⊙              |
| Percentage of vegetation cover (%)          | ⊙                                 | ⊙               | ⊙              |
| The thickness of vegetation cover (m)        | ⊙                                 | ⊙               | ⊙              |
| Watershed area (m²)                          | ⊙                                 | ⊙               | ⊙              |
| Height of toe-excavation (m)                 | ⊙                                 | ⊙               | ⊙              |
| Change in slope inclination (◦)              | ⊙                                 | ⊙               | ⊙              |
| Precipitation (mm)                           | ⊙                                 | ⊙               | ⊙              |
| Groundwater level (m)                        | ⊙                                 | ⊙               | ⊙              |
| Soil inclination (x-axis) (mm)               | ⊙                                 | ⊙               | ⊙              |
| Soil inclination (y-axis) (mm)               | ⊙                                 | ⊙               | ⊙              |
| Retaining wall tilt (x-axis) (sec)           | ⊙                                 | ⊙               | ⊙              |
| Retaining wall tilt (y-axis) (sec)           | ⊙                                 | ⊙               | ⊙              |

⊙ Significant correlation at 0.01 significance level (two-tail).

than those of the training process. Notably, the excellent values of (0.988) provided by the SOS-LSSVR model close to 1 exhibit that the mapped function of anchor load agrees with the fluctuation of the actual part of anchor load. Since SOS-LSSVR had the best results for estimating the load on ground anchors, this model is employed for further analysis in the next steps.

5. Result Analysis and Discussion

5.1 Load estimation of monitoring sections

The monitoring sections 3-7, 3-8, 3-9, 3-10, 6-3, and 6-4, which did not have ground anchor load cells, were used for load inference. The base day was set on 30 June 2015, with the inputs and outputs shown in Table 10 and Table 11.
The output values for monitoring sections 3-7, 3-9, 3-10, 6-3, and 6-4 were 0.378, 0.401, 0.498, 0.356, and 0.175, used in the inverse calculation for the forecasted ground anchor load. The loads were subsequently determined as 52.011T, 52.364T, 53.825T, 51.679T, and 48.931T, respectively. Those estimated loads were below the attention threshold value of 55T. Furthermore, the standard deviations were around 0.02; therefore, the chance of exceeding the attention threshold would be less than 1%. The highest output value found at monitoring section 3-8 was 0.522, which is inverted to 54.654T, relatively close to the attention threshold value. Nevertheless, the chance of exceeding the attention threshold would still be meager since the standard deviation was also found to be 0.02.

5.2 Measures to be undertaken

A ground anchor can be considered as a single force member; therefore, its load bearing is a direct reflection of the condition of the artificial slope. When the ground anchor load reaches the originally designed management values (in this case, they were the attention threshold of 55T, the alert threshold of 60T, and action threshold of 90T), the responsible authorities should immediately undertake countermeasures. Such measures may include a comprehensive assessment of slope safety, increased inspection and patrolling of the site, and making emergency responses and remedies according to a predetermined emergency plan. The following is a more detailed description of these measures.

When the load on a ground anchor reaches the management values, a preliminary safety assessment should be undertaken immediately. In this assessment, the readings of the slope inclinometers, retaining wall tiltmeters, water level observation well, and udometer will be checked to determine whether either of the devices displays readings that suggest a trend of displacement toward one general direction. If the readings of the ground anchor load cell reach the management value, and the readings of both the inclinometer and tiltmeter also show a conspicuous trend or have reached their respective management values, an anomaly must have occurred to the artificial slope. Under such a circumstance, a slope stability analysis must be undertaken without delay to determine how dangerous the situation is regarding the retaining wall’s safety.

As far as increased inspection and patrolling of the site is concerned, for anchored artificial slopes, this involves slope inspection, retaining wall inspection, drainage inspection, and ground anchor inspection. The authorities are advised to conduct these inspections regularly according to a predetermined inspection plan, and also set up a special examination and patrolling rounds during and after a torrential rain or earthquake.

This study employed SOS-LSSVR as the inference model to estimate, with too high forecasting accuracy (MAPE < 10%), the ground anchor loads to monitoring sections 3-7 to 3-10, 6-3, and 6-4, which were not equipped with ground anchor load cells. The estimated values show that none of the sections reached the attention threshold of 55T, although the load at monitoring section 3-8 was 54.654T, which was relatively close to 55T.

After the ground anchor loads at the monitoring sections that were not equipped with a ground anchor load cell had been estimated, a comprehensive safety assessment was conducted. The purpose was to determine whether either of the existing monitoring devices, such as the inclinometer and tiltmeter, had displayed readings that had reached the attention threshold, or had exhibited a trend of displacement toward one general direction. The assessment results for the individual monitoring sections and advice for subsequent actions are as below.

Regarding monitoring sections 3-7, 3-9, 3-10, 6-3, and 6-4, assessment results indicated that the maximum cumulative displacements of the inclinometer and tilt meter un-reached their respective attention thresholds, nor had exhibited any conspicuous trends. The highest groundwater levels observed through the water level observation well were 17.43, 11.21, 18.50, 12.48, and 1.52 m underground, respectively. Also, the estimated ground anchor loads were 52.011, 52.363, 53.825, 51.679, and 48.931T, which were below the attention threshold (Fig. 8). Therefore, the artificial slopes were assessed to be in safety status, and the given advice was to maintain the regular site inspection and patrolling.

In terms of monitoring section 3-8, the assessment gives the same result with the monitoring as mentioned above. The highest groundwater level observed through the water level observation well was 14.01 m underground. However, the estimated ground anchor load was 54.654T given by SOS-LSSVR, which is likely to increase when suffering a storm or an earthquake. Note that Taiwan is located in circum-Pacific seismic zone, and thus usually suffers typhoons, convection rain, and tremor. Therefore, a slope stability analysis was recommended for the artificial slope to determine its factor of safety. The authorities were advised to more frequently maintain regular site inspection and patrolling for the ground anchor of this section.

The following is a more detailed description of these measures.

| No. | Input variable | Factor |
|-----|----------------|--------|
| 1   | F1             | Slope height (°) |
| 2   | F2             | Slope profile (°) |
| 3   | F3             | The angle between slope aspect and dip direction (°) |
| 4   | F4             | Bedrock condition (%) |
| 5   | F5             | The thickness of weathered rock blocks (m) |
| 6   | F6             | The thickness of vegetation cover (m) |
| 7   | F7             | Watershed area (m²) |
| 8   | F8             | Height of toe-excavation (m) |
| 9   | F9             | Retaining wall tilt (x-axis) (sec) |
| 10  | F10            | Retaining wall tilt (y-axis) (sec) |
| 11  | F11            | Soil inclination (y-axis) (mm) |
| 12  | F12            | |
Table 6: Data samples of the analyzed dataset.

| No. | The angle aspect and dip (°) | The slope profile | The thickness of exposed bedrock blocks (% of estimated load) | The thickness of vegetation cover (m) | The height of the water table (m) | The watershed excavation area (m²) | The ground level inclination (°) | The change in slope inclination (°) | The load cell installation (sec) | The lift-off test (sec) | The length of the retaining wall (m) | The wall thickness (mm) | The slope (°) | The height of the wall tilt (m) |
|-----|-----------------------------|-------------------|---------------------------------------------------------------|-----------------------------------|---------------------------------|---------------------------------|-------------------------------|---------------------------------|-------------------------------|----------------|----------------------------------|---------------------|----------------|-----------------------------|
| 1   | 180                         | 21.1              | 19.0                                                          | 4.0                              | 2.0                             | 280.0                           | 9.0                           | 1.0                             | 10.0                          | 10.0           | 461.0                            | 32.6                | 261.0| 197.0                       |
| 2   | 180                         | 21.1              | 19.0                                                          | 4.0                              | 2.0                             | 280.0                           | 9.0                           | 1.0                             | 10.0                          | 10.0           | 461.0                            | 32.6                | 261.0| 197.0                       |
| 3   | 180                         | 21.1              | 19.0                                                          | 4.0                              | 2.0                             | 280.0                           | 9.0                           | 1.0                             | 10.0                          | 10.0           | 461.0                            | 32.6                | 261.0| 197.0                       |
| 4   | 180                         | 21.1              | 19.0                                                          | 4.0                              | 2.0                             | 280.0                           | 9.0                           | 1.0                             | 10.0                          | 10.0           | 461.0                            | 32.6                | 261.0| 197.0                       |
| 5   | 180                         | 21.1              | 19.0                                                          | 4.0                              | 2.0                             | 280.0                           | 9.0                           | 1.0                             | 10.0                          | 10.0           | 461.0                            | 32.6                | 261.0| 197.0                       |

5.3 Proposed system for actual practice

Although the load on the ground anchor is measured with the electrical load cells or by lift-off test, load cells can only survive for a limited time when used in an outdoor environment (Liao, 2018). The lift-off test is relatively simple in principle but often has site accessibility problems when implemented on the existing anchor. Due to the reasons as mentioned above, both the load cell installation and the lift-off test cannot be carried out in large numbers. Moreover, monitoring and maintaining a large number of load cells at the same time may be an overwhelming task.

To make the inference model for artificial slope ground anchor loads more practical, a system implementing this model was developed for the responsible authorities. The readings of the monitoring devices are collected in the data logger and general packet radio service module in the outdoor monitoring station, and then forwarded to the server through wireless transfer. After the data are received and stored by the server, the responsible authorities can read the data and receive warning information on the web-based interface.

The collected case data will be normalized and fed to the artificial intelligence inference model for the forecast of ground anchor loads at slopes without ground anchor load cells. With reasonable forecast accuracy, the responsible authorities will determine the measures and actions to be taken following the assessment of the artificial intelligence inference model.

6. Conclusions and Suggestions

Slope stability monitoring and risk assessment are essential to provide early warning information of landslide. The load on ground anchors has been identified as a critical indicator for landslide prediction. This study has evaluated possible influential factors of ground anchor loads and developed inference models to estimate the ground anchor loads in artificial slopes. After applying R, RMSE, MAE, and MAPE on the many inference models, SOS-LSSVR has emerged with the highest general accuracy for ground anchor loads. The SOS-LSSVR model has a MAPE value of 9.10% and a correlation coefficient R of 0.988, indicating that the estimated load on ground anchors given by SOS-LSSVR is reliable. Therefore, responsible authorities rely on the estimated load values to quickly provide a preliminary assessment of an artificial slope to have proper follow-up actions.

According to the inference of SOS-LSSVR, which was conducted with reasonable forecast accuracy, none of the ground anchor loads on the six monitoring sections un-equipped with ground anchor load cells had reached the attention threshold (55T). In the subsequent comprehensive slope safety assessment, the readings of the other monitoring devices on the six areas were also found below their respective attention thresholds. Therefore, the six areas are considered to be in a stable state. However, an increase in the regular inspection and patrolling operations is advisable and necessary for preventing the occurrence of anchor failure, especially after typhoons or earthquakes.

In case of applying the SOS-LSSVR for other areas with totally different geological properties, users are strongly suggested to collect a new dataset from the local intrinsic and extrinsic conditions (e.g. slope aspects, height) and retaining wall system, to precisely determine the influential factors for efficiently capturing the function of the load on the ground anchor. The data imbalance issue should be checked before carrying out the
Table 7: Parameter settings for AI inference models.

| AI models | Parameters | Setting references |
|-----------|------------|--------------------|
| LR        | Eliminate collinear attributes = true Minimal = false Ridge = $10^{-8}$ | Corporation (2013) |
| SVR       | Regulation parameter $C = 10$ RBF Kernel parameter $\gamma = 0.1$ | Corporation (2013) |
| LSSVR     | Regulation parameter $\sigma = 1$ RBF Kernel parameter $\gamma = 1$ | Cheng, Prayogo, and Wu (2018) |
| RBFNN     | Spread $\sigma = 1$ Maximum neuron = 16 | Cheng and Cao (2016) |
| BPNN      | Alpha $\alpha = 0.9$ Initial $\mu = 0.3$ High $\mu = 0.1$ Low $\mu = 0.01$ $\mu$ decay = 30 Hidden layers = 20-15-10 Persistence = 200 | Corporation (2013) |
| SOS-LSSVR | $\gamma$ boundary = $10^{-8} - 10^{8}$ $\sigma$ boundary = $10^{-5} - 10^{5}$ Population size = 25 Maximum number of iterations = 100 | Cheng et al. (2018) |

Table 8: Performance evaluation criteria.

| Performance measure | Formula |
|---------------------|---------|
| Mean absolute percentage error (MAPE) | $\frac{1}{n} \sum_{i=1}^{n} \left| \frac{y - y'}{y} \right| \times 100\%$ |
| Mean absolute error (MAE) | $\frac{1}{n} \sum_{i=1}^{n} |y - y'|$ |
| Root mean squared error (RMSE) | $\sqrt{\frac{1}{n} \sum_{i=1}^{n} (y - y')^2}$ |
| Coefficient of correlation ($R$) | $\frac{\sum_{i=1}^{n} y_i y'_i - (\sum_{i=1}^{n} y_i)(\sum_{i=1}^{n} y'_i)}{\sqrt{\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2} \sqrt{\sum_{i=1}^{n} y'_i^2 - (\sum_{i=1}^{n} y'_i)^2}}$ |

Table 9: Ten-fold cross-validation result of the AI inference models.

| Original value | MAPE | RMSE | MAE | $R$ | Ranking |
|---------------|------|------|-----|-----|---------|
|               | Training | Test | Training | Test | Training | Test | Training | Test | Training | Test |        |
| LR            | 17.11% | 46.95% | 0.5039 | 1.3141 | 0.6740  | 1.6195 | 0.9628  | 0.8388 | 8       |
| SVR           | 8.02%  | 33.89% | 0.3487 | 0.8598 | 0.5722  | 1.1093 | 0.9734  | 0.9060 | 7       |
| RBFNN         | 11.24% | 9.56%  | 0.3954 | 0.3431 | 0.5557  | 0.4729 | 0.9755  | 0.9830 | 3       |
| BPNN          | 11.64% | 11.16% | 0.5177 | 0.5659 | 0.2646  | 0.2848 | 0.9843  | 0.9804 | 5       |
| LSSVR         | 13.05% | 13.70% | 0.4335 | 0.5179 | 0.2949  | 0.3134 | 0.9907  | 0.9859 | 4       |
| ESIM          | 9.75%  | 10.98% | 0.3062 | 0.4508 | 0.2152  | 0.2413 | 0.9949  | 0.9873 | 2       |
| SOS-LSSVR     | 7.84%  | 9.10%  | 0.2429 | 0.4477 | 0.1699  | 0.2166 | 0.9969  | 0.9883 | 1       |

model construction of ground anchor loads. A substantial gap between the number of cases reaching and un-reaching management values will compromise predicting the load on ground anchors. Then, the new dataset should be collected to train and construct a new inference model per the methods and framework described herein, which is also considered the future work of the present study to affirm the performance of the SOS-LSSVR model. The future work will further benchmark the performance of SOS-LSSVR against newly published approaches on predicting load on ground anchors to help users get insightful information on the merits of each model.

The users are suggested to regularly update their dataset for increasing the generalization of the SOS-LSSVR model. In summary, this paper contributes a reliable method to the core body of knowledge for the load-on-ground-anchor prediction task that achieves the United Nations Goals for Sustainability, in particular the GOAL 11, which aims at making cities and human settlements inclusive, safe, resilient, and sustainable.
Figure 7: Presentation of AI inference models’ performance.

Table 10: Inputs for monitoring sections.

| Input variables                                      | Monitoring sections |
|------------------------------------------------------|---------------------|
|                                                      | 3-7  | 3-8  | 3-9  | 3-10 | 6-3  | 6-4  |
| Slope height (°)                                     | 91.88| 91.92| 93.67| 93.81| 52.69| 62.78|
| Slope profile (°) (+10⁻²)                           | −0.087| −0.087| 0.145| 0.145| −0.309| −0.309|
| The angle between slope aspect and dip direction (°) | 3.20 | 2.80 | 8    | 11   | 5    | 6.6  |
| Bedrock condition (%)                                | 73.41| 72.43| 76   | 81.17| 70   | 74   |
| The thickness of weathered rock blocks (m)           | 0.30 | 0.60 | 1    | 1.50 | 3.9  | 1.6  |
| The thickness of vegetation cover (m)                | 2.10 | 2.10 | 1.8  | 1.80 | 1.5  | 1.6  |
| Watershed area (m²)                                  | 7379.92| 7379.92| 9275.08| 9275.08| 4105.94| 5601.38|
| Height of toe-excavation (m)                         | 8.40 | 8.70 | 10.80| 12.60| 7.90 | 7.3  |
| Groundwater level (m)                                | 2.93 | −5.803| −4.62| −7.369| −16.603| −7.538|
| Retaining wall tilt (x-axis) (sec)                    | −259.9| 15.923| 559.4| −175.58| 17.322| 67.9  |
| Retaining wall tilt (y-axis) (sec)                    | −440.63| −64.59| 633.60| −198.39| −53.77| −46.47|
| Soil inclination (y-axis) (mm)                        | −1.43 | 0.384| 4.84 | −0.17| −0.759| 0.352|

Table 11: Output for monitoring sections.

| Output                                      | Monitoring sections |
|---------------------------------------------|---------------------|
| Output value                                | 3-7  | 3-8  | 3-9  | 3-10 | 6-3  | 6-4  |
| Forecasted ground anchor load (t)           | 0.378| 0.553| 0.401| 0.498| 0.356| 0.175|
| Assessment                                  | 52.011| 54.654| 52.364| 53.825| 51.679| 48.931|

Assessment

Below the attention threshold (55T)
7. Code Availability

The code of the developed model for this study is available at: https://github.com/Minh-Tu-Cao/SOS-LSSVM-Matlab.

Conflict of Interest Statement

None declared.

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