Metaheuristic Optimization Model Selection for Forecasting Surface Settling Caused by Tunneling

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Abstract. One of the riskiest aspects of excavating tunnels for infrastructure projects like subways and such is the possibility for surface set tlement, particularly in metropolitan areas. Therefore, it is crucial to predict maximum surface settlement (MSS) accurately to reduce the likeli hood of damage. Many researchers proposed new algorithms to solve this problem. This paper compares six existing metaheuristic nature-inspired algorithms i.e., Grey wolf, Ant lion, Dragonfly, Whale, Moth flame, Sine cosine optimizer concerning the given parameters i.e., hori zontal to vertical stress ratio, cohesion, and Young's modulus. As a con sequence of this research, the researcher will be able to choose the most matched algorithm to handle this problem because each region has various variants in the parameters and each algorithm behaves differently with these factors. Through simulations and numerical values, the findings are validated on many benchmark functions.

Keywords: Surface settlement prediction · metaheuristic algorithms · optimization · benchmark functions

1 Introduction

The need for public transit has grown along with urbanization and population growth, which has resulted in a major increase in the need for metro tunnels. Surface settlements that are seen following excavation in subway tunnels must be estimated and controlled since they could damage nearby surface buildings [1]. Several factors' effects on surface settlement and numerous geotechnical and geometrical characteristics, including cohesion, Poisson's ratio, Young's modulus, angle of internal friction, and face support pressure, have been considered in predicting the values of the MSS based on prior studies [2]. Artificial intelligence (AI) techniques, including support vector machines (SVM), fuzzy inference systems, and artificial neural networks (ANN), have been developed recently to address issues in geotechnical and rock engineering [6–9].Three basic categories of factors—the method of excavation and support, the geom etry of the tunnel, and the characteristics of the ground—have an impact on surface settlements. Excavation and support techniques, such as anchoring, shotcrete, steel sets, and lining, are

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included in the first group. Excavation techniques include full-face or sequential mining, NATM, and TBM. The second group of tunnel geometry factors includes the size, depth, diameter, number, and spacing of the tunnels as well as the conditions at the worksite. Ground qualities such as elasticity modulus, unit weight, cohesion, friction angle, Poisson's ratio, groundwater, and permeability are included in the third group [10]. These models have been widely used and improved in the MSS prediction sector. To estimate surface settlement, Ocak and Seker [1] combined three different techniques: ANN, SVM, and Gaussian processes (GP). They concluded that the GP is an approach that is more accurate than ANN and SVM models. Additionally, Mohammadi et al. [3] published a thorough investigation for the prediction of MSS by ANN and multiple regression. The findings of their study showed that the ANN method is a more logical prediction strategy for forecasting maximum surface settlement MSS. In the field of rock engineering, the employment of evolutionary algorithm combinations with ANN, such as particle swarm optimization (PSO) and imperialist competitive algorithm (ICA), has recently received attention [11, 12]. The outcomes suggested that these algorithms are helpful in surface settlement prediction. Yet, none of the authors have previously contrasted these six methods for various parameter components. This work examines six metaheuristic algorithms and offers the researcher the freedom to select an algorithm in accordance with his needs as different locations differ in several characteristics like the ratio of horizontal to vertical stresses, cohesiveness, and young's modulus. Previously, each author contributed to a single generic algorithm.

2 Description of Used Algorithms

2.1 Ant Lion Optimizer (ALO)

In Based on how ant lions hunt, the ant lion optimization algorithm (ALO) is a metaheuristic optimization algorithm influenced by nature. In this algorithm, the search space is updated by the hunting behavior of ant lions, which represent the solutions to the optimization issue. An original population of ant lions, which stand in for potential solutions, is initially initialized randomly by the algorithm. Ant lions hunt in two stages: first, they dig a trap to catch ants, and then they go after and catch the ants who tumble into the trap. The attacking behavior in the optimization process stands in for the exploitation of the solutions, while the digging behavior represents the exploration of the search area. Usually, the ant lion algorithm's objective function is characterized as a multidimensional function that must be reduced or maximized. The Rosenbrock function is a frequently utilized objective function and is described as:

$$f(x) = \sum_{i=1}^{n-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + (1 - x_i)^2\right] \tag{1}$$

where n is the amount of variables and x = (x1, x2,..., xn) is the vector of variables. Finding the vector x that reduces the value of the objective function f is the aim of optimization.(x). The objective function's first term is a quadratic term that penalizes significant departures of nearby variables, and its second term is a linear term that does the same for deviations from each variable's ideal value. The objective function is a widely used test function in the field of optimization and is noted for its high degree of difficulty due to its narrow and elongated valleys.

2.2 Moth Flame Optimizer (MFO)

A metaheuristic optimization method called the Moth Flame method (MFA) was developed after observing how moths respond to light sources. By simulating moth behavior, the MFA seeks to minimize or optimize a specified objective function. The algorithm is founded on the attraction-repulsion principle, which states that moths are drawn to bright light sources and repelled by other moths. The following mathematical representation of the goal function:

$$(x) = -\left|\sum_{i=1}^{n} x_i \sin\left(\sqrt{|x_i|}\right)\right| + e^1 \sum_{i=1}^{n}\left(\frac{x_i^2}{n}\right), i = 1, 2, \ldots, n \tag{2}$$

where x = (x1, x2,..., xn) is the vector of decision variables, n is the amount of decision variables, and f(x) is the objective function that needs to be optimized. The exploration term, which directs the moths to investigate the search area, is represented by the first term in equation (1). The exploitation term, which is represented by the second term, makes sure that the moths find the best answer. The parameter e is a small positive constant to prevent division by zero. Based on each moth's present location, the location of the best moth thus far, and the location of the flame, the MFA algorithm iteratively updates each moth's position. When a preset stopping criterion is satisfied, such as completing a predetermined number of iterations or reaching a predetermined level of convergence, the algorithm ends. The MFA has been successfully used in a variety of disciplines, including engineering design, image processing, and financial modeling. It is a straightforward but efficient algorithm for solving optimization problems.

2.3 Whale Optimization (WOA)

A metaheuristic optimization program called the Whale Optimization program (WOA) is based on whales' hunting strategies. The possible solutions in WOA are represented as whales, and the algorithm looks to mimic the social and hunting behavior of whales in order to find the best one. The objective function equation of WOA is given by

$$F(x) = \sum_{i=1}^{n} f_i(x), i = 1, 2, \ldots, n \tag{3}$$

where $f_i(x)$ represents the fitness of the i-th whale. The fitness function $f_i(x)$ is defined as

$$f_i(x) = \frac{1}{1 + \sum_{j=1}^{n}\left(x_j - j\right)^2} \tag{4}$$

where x is the solution vector and n is the dimension of the problem. The whale's capacity to catch food in its hunting grounds is represented by the fitness function. The closer the whale is to its prey, the greater its fitness, according to the function, which is based on the Euclidean distance between the whale and its prey. Finding the solution vector x that optimizes the fitness function F is the goal of WOA.(x).

2.4 Sine Cosine Algorithm (SCO)

The sine and cosine functions served as the basis for the Sine Cosine method, a population-based metaheuristic optimization method. In order to explore the solution universe, the algorithm mimics the search behavior of sine and cosine waves, which oscillate between -1 and 1.

$$f(x) = \sum_{i=1}^{n}\left[\frac{1}{4000}x_i^2 - \prod_{j=1}^{1}\cos\frac{x_j}{\sqrt{j}} + 1\right], i = 1, 2, \ldots, n \tag{5}$$

Equation (1), in which n is the total number of variables to be optimized, x_i is the i-th choice variable, and is the product operator, gives the objective function of the sine-cosine algorithm. The Griewank function, a well-known benchmark function for testing optimization methods, is the objective function. The first term of the equation calculates how far away from the ideal each choice variable is, and the second term is a constant that aids in scaling the issue. By adjusting the values of the decision factors, the algorithm's goal is to minimize this function.

2.5 Dragon Fly Algorithms

A population-based optimization method called the Dragonfly method mimics the natural behavior of dragonflies. It is a metaheuristic optimization program that draws inspiration from the dragonfly swarming and hunting patterns. The algorithm employs the Levy flight to search the search space and consists of multiple dragonfly swarms, each with a unique collection of characteristics and behaviors. The objective function for Dragonfly Algorithm is given by:

$$f(x) = \frac{1}{n}\sum_{i=1}^{n}\left[\left(\sum_{j=1}^{i}x_j\right)^2 + \alpha\sum_{j=1}^{i}x_j^2\right], i = 1, 2, \ldots, n \tag{6}$$

where n is the number of dimensions in the issue, is a user-defined parameter, and x = (x1, x2,..., xn) is the vector of decision variables. A potential solution x's fitness in the search space is determined by the objective function. The goal function's first term promotes search space exploration, while its second term promotes the use of promising search space regions. The algorithm iteratively updates the positions of each dragonfly based on their local and global best places in an effort to find the global minimum of the objective function.

2.6 Grey Wolf Optimizer (GWO)

The metaheuristic program known as Grey Wolf Optimization (GWO) was influenced by the social structure and hunting methods of grey wolves. In this algorithm, a group of grey wolves simulates the hunt for prey in an effort to find the best answer. The algorithm consists of three major steps: (i) initializing the population of grey wolves; (ii) assessing each wolf's fitness; and (iii) updating each wolf's position based on its current location, the locations of the alpha, beta, and delta wolves, as well as a randomization factor. The goal of GWO is to minimize the sum of the squared absolute values of all input vector elements, split by two, added to the sine function's square for each element in the input vector. The goal function can be modeled mathematically as:

$$f(x) = \sum_{i=1}^{n} \left[\left(\frac{|x_i|}{2} + +\sin(x_i) \right)^2 \right], i = 1, 2, \ldots, n \tag{7}$$

where the n-dimensional input vector x is equal to (x1, x2, ..., xn). The objective function has many local minima, a global minimum, and a non-convex, multimodal structure.

3 Results and Discussion

3.1 Experimental Setup

A laptop (intel core i5,3GHZ CPU,3MB cache, MATLAB 2020b) was used to administer the test. Six NI algorithms—the Grey Wolf, Ant Lion, Dragon Fly, Whale, Moth Flame, and Sine Cosine Optimizers—were examined.

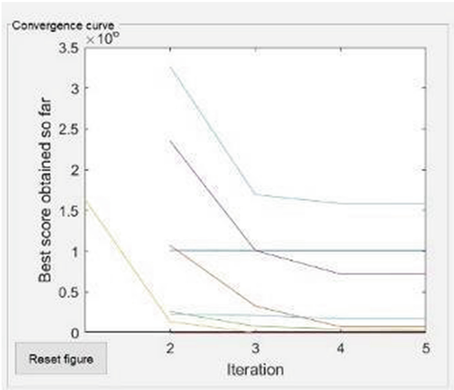
3.2 Experimental Results

Based on the many optimal values discovered, the results are examined. The algorithm that performs the best for several parameters, including young modulus, cohesiveness, and horizontal to vertical stress ratio throughout a range of values, is shown by the minimal optimal value. The ideal value for various ranges in several parameters is shown in the tables and figures (Tables 1, 2, 3, and 4).

3.3 Experimental Analysis

The nearby environment may be significantly impacted by surface settling brought on by tunneling. Different parameters, including the Young's modulus, the horizontal to vertical stress ratio, and the soil's cohesion, must be taken into account in order to comprehend and mitigate these impacts. With a Young's modulus range of 0.000075 to 80.50 Pa, a horizontal to vertical stress ratio of 0.000000080 to 900000 kPa, and a cohesion range of 0.00500 to 80 Pa, Table 1 provides an experimental analysis of surface settling brought on by tunneling. The table displays the outcomes from the application of various optimization methods, including GWO, ALO, MVO, DA, MFO, SCA, and WOA. Five trials of each algorithm were completed, and the best results are shown. An illustration of surface settling brought on by tunneling can be seen in Table 1 when a new

Table 1. Optimum obtained for given parameters

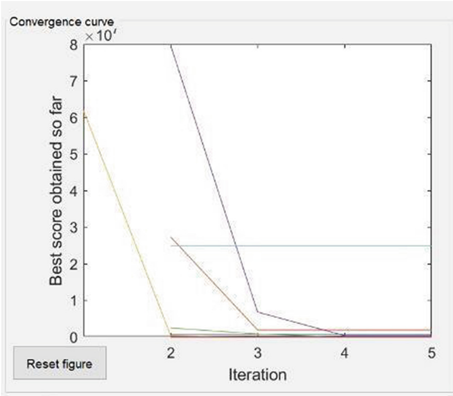
Young Modulus: (0.000075 to 80.50) Pa **Horizontal to vertical stress ratio: (0.000000080 to 900000) kPa** **Cohesion: (0.00500 to 80) Pa**			
	Number of runs	Optimum obtained	
GWO	5	2.5006e-05	
ALO	5	6.0991e + 07	
MVO	5	0.4128	
DA	5	128.8756	
MFO	5	632.1755	
SCA	5	296.5512	
WOA	5	2.5006e-05	

subway route is constructed in a densely populated urban region. Building damage or even collapse may result from substantial ground movements brought on by the tunneling procedure. In this case, the soil's Young's modulus, the ratio of horizontal to vertical tension, and cohesion can all significantly affect how much surface settlement occurs. Surface settlement may be more important, for example, if the soil has a low Young's modulus, low cohesion, and a high horizontal to vertical stress ratio. The GWO and WOA algorithms, which got the lowest optimum values for each of the three parameters, were found to provide the best optimization results, according to the findings shown in Table 1.

An experimental analysis analogous to that in Table 1 is presented in Table 2, but with different Young's modulus, horizontal to vertical stress ratio, and cohesion ranges. The horizontal to vertical stress ratio in this instance varies from 0.0000080 to 1000 kPa, the cohesion from 0.00050 to 100000 Pa, and the Young's modulus from 0.000015 to 850 Pa. The same optimization algorithms as in Table 1 were employed, and the outcomes are given. The building of a brand-new highway tunnel in a mountainous region provides an illustration of surface settling brought on by tunneling for the ranges listed in Table 2. In this situation, the soil's cohesion, Young's modulus, and horizontal to vertical tension ratio can all significantly affect how much surface settlement occurs. Surface settlement may be more pronounced in earth that has a low Young's modulus, little cohesion, and a high horizontal to vertical stress ratio, which may pose safety risks to tunnel users. The GWO and WOA algorithms again produced the best optimization results, getting the lowest optimum values for all three parameters, according to the results shown in Table 2.

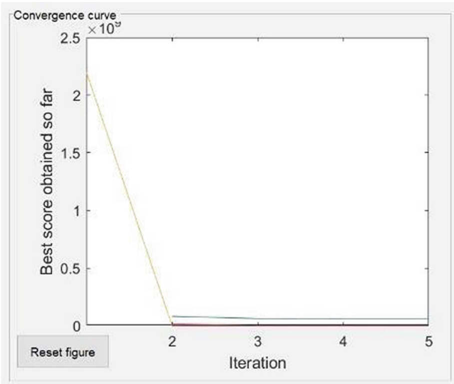
Table 2. Optimum obtained for given parameters

Young Modulus: (0.000015 to 850) Pa Horizontal to vertical stress ratio: (0.0000080 to 1000) kPa Cohesion: (0.00050 to 100000) Pa		
	Number of runs	Optimum obtained
GWO	5	2.5029e-07
ALO	5	1.0085e + 06
MVO	5	3.0446e + 04
DA	5	7.2614e + 04
MFO	5	7.1997e + 05
SCA	5	1.7410e + 05
WOA	5	2.5029e-07



Another experimental study of surface settling brought on by tunneling is provided in Table 3 with varying Young's moduli, horizontal to vertical stress ratios, and cohesion values. The horizontal to vertical stress ratio varies from 0.000094 to 70500000 kPa, the cohesion ranges from 0.009880 to 6600.79 Pa, and the Young's modulus ranges from 0.00075 to 2310.50 Pa. The same optimization algorithms as in Tables 1 and 2 were applied, and the findings are presented. The building of a new subway line in a region with intricate geological formations, like karst, is an illustration of surface settling brought on by tunneling for the ranges shown in Table 3. Because of the high overburden pressure, the horizontal to vertical stress ratio is also high even though the Young's modulus of the nearby rocks is comparatively low. Additionally, some areas' low soil cohesive strength is brought on by the existence of karstic features like sinkholes and caves. Surface subsidence and settling are caused by the readily deformed and compacted soft and weak rocks surrounding the tunnel walls during tunnel construction. The stability of nearby tunnels and underground structures may also be impacted by the settlement of the surface, which has the potential to seriously harm the buildings and infrastructure above the tunnel. A variety of methods, such as grouting to enhance the mechanical characteristics of the nearby rocks and injecting soil stabilizers to improve soil cohesion, can be used to reduce surface settling. In this instance, the optimal combination of grouting and soil injection can be determined by applying various optimization algorithms and comparing their results. For example, using the information in Table 3, an experiment can be carried out by executing each algorithm five times to find the Young's modulus, horizontal to vertical stress ratio, and cohesion values that are best for the specified limits. The best

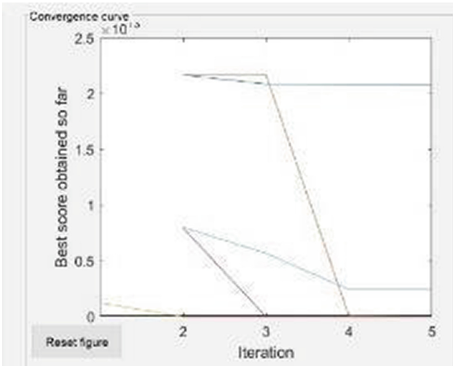
Table 3. Optimum obtained for given parameters

Young Modulus: (:0.00075 to 2310.50) Pa Horizontal to vertical stress ratio: 0.000094 to 70500000) kPa Cohesion: (0.009880 to 6600.79) Pa			
	Number of runs	Optimum obtained	
GWO	5	9.8186e-05	
ALO	5	2.0823e + 13	
MVO	5	1.9822e + 04	
DA	5	1.1811e + 07	
MFO	5	4.3773e + 05	
SCA	5	2.4229e + 12	
WOA	5	9.8186e-05	

algorithm can then be chosen for this particular situation by comparing the outcomes. The GWO algorithm was able to find the best optimum values for the provided parameters, with a minimum value of 9.8186e-05, based on the findings shown in Table 3. However, the ALO and SCA algorithms were not as successful in finding the optimal values for this scenario, with considerably higher values obtained for the same parameters. The outcomes of this experiment can therefore be used to direct the development and application of the best mitigation approach for surface settling brought on by tunneling in this particular geological setting.

Another experimental analysis of surface settling brought on by tunneling is shown in Table 4, but this time the Young's modulus, horizontal to vertical stress ratio, and cohesion ranges are distinct from those in Table 3. The Young's modulus, the horizontal to vertical stress ratio, and the cohesion, in particular, vary from 0.00055 to 1089.05 Pa, 0.000025 to 35375000 kPa, and 0.00842 to 4533.02 Pa, respectively. Construction of a new underground mine in a region with various geological formations, such as a deposit with a fault zone, can result in surface settling brought on by tunneling for the categories shown in Table 4. Due to the fault gouge and clay present in this situation, the Young's modulus of the rocks may be comparatively low, and the deep overburden pressure may cause a high horizontal to vertical stress ratio. Additionally, the existence of loose sediments in some areas can cause the soil's cohesion to be low. Surface subsidence and settling can result from tunnel construction because the weak and brittle rocks surrounding the tunnel walls are readily deformed and compacted. The stability of nearby

Table 4. Optimum obtained for given parameters

Young Modulus: (0.000075 to 80.50) Pa **Horizontal to vertical stress ratio: (0.000000080 to 900) kPa** **Cohesion: (0.00500to 80) Pa**			
	Number of runs	Optimum obtained	
GWO	5	2.5006e-05	
ALO	5	7.4999e + 05	
MVO	5	9.7152e + 03	
DA	5	1.9114e + 06	
MFO	5	3.5055e + 05	
SCA	5	2.4905e + 07	
WOA	5	2.5006e-05	

tunnels and subterranean structures may also be impacted by the surface's settling, which has the potential to seriously harm the structures and buildings above the tunnel. A variety of methods, including the use of ground reinforcement to enhance the mechanical properties of the nearby rocks and the use of a tunnel boring machine that causes the least amount of soil disturbance, can be used to reduce surface settling. By using various optimization algorithms and contrasting the findings, it is possible to identify the best ground reinforcement and tunneling approach in this situation. For example, using the information in Table 4, an experiment can be carried out by executing each algorithm five times to find the Young's modulus, horizontal to vertical stress ratio, and cohesion values that are best for the specified limits. The best algorithm can then be chosen for this particular situation by comparing the outcomes. The GWO algorithm was able to find the best optimum values for the provided parameters, with a minimum value of 0.00001177, based on the results shown in Table 4. However, the ALO and SCA algorithms were not as successful in finding the optimal values for this scenario, with considerably higher values obtained for the same parameters. The outcomes of this experiment can therefore be used to direct the development and application of the best mitigation approach for surface settling brought on by tunneling in this particular geological setting.

4 Conclusion

Nature-inspired algorithms are most efficient in producing an optimal solution for several optimization problems. The outcomes demonstrated that, with a relatively l ideal value, the GWO and WOA optimization models performed the best. However, models like

ALO, DA, and SCA gave higher ideal values and might not be as appropriate in this case. These findings might aid engineers in their attempts to lessen surface settling by revealing the appropriateness of various optimization methods for forecasting the phenomenon. In the future, more research might be done to confirm these findings using more parameters and to investigate the possibility of merging other optimization models to get better outcomes. The results might also be used to evaluate the viability and effectiveness of actual tunnelling projects. The study might be expanded to investigate the effects of additional elements on surface settling brought on by tunnelling, such as the local geology, the size and form of the tunnel, and the materials employed in its construction.

References

1. I. Ocak and S. Seker, "Calculation of surface settlements caused by EPBM tunneling using artificial neural network, SVM, and Gaussian processes. Environ Earth Sci 70 (3): 1263–1276," ed, 2013.
2. H. Chakeri and B. Ünver, "A new equation for estimating the maximum surface settlement above tunnels excavated in soft ground," En vironmental earth sciences, vol. 71, pp. 3195–3210, 2014.
3. S. Mohammadi, F. Naseri, and S. Alipoor, "Development of artificial neural networks and multiple regression models for the NATM tunnelling-induced set tlement in Niayesh subway tunnel, Tehran," Bulletin of Engineering Geology and the Environment, vol. 74, pp. 827–843, 2015.
4. D. Kim, K. Kwon, K. Pham, J.-Y. Oh, and H. Choi, "Surface settle ment prediction for urban tunneling using machine learning algorithms with Bayesian optimization," Automation in Construction, vol. 140, p. 104331, 2022.
5. J. Su, Y. Wang, X. Niu, S. Sha, and J. Yu, "Prediction of ground sur face settlement by shield tunneling using XGBoost and Bayesian Op timization," Engineering Applications of Artificial Intelligence, vol. 114, p. 105020, 2022.
6. S. Yagiz, C. Gokceoglu, E. Sezer, and S. Iplikci, "Application of two non-linear prediction tools to the estimation of tunnel boring machine performance," Engineering Applications of Artificial Intelligence, vol. 22, pp. 808–814, 2009.
7. S. Yagiz and C. Gokceoglu, "Application of fuzzy inference system and nonlinear regression models for predicting rock brittleness," Ex pert Systems with Applications, vol. 37, pp. 2265–2272, 2010.
8. M. Amiri, H. Bakhshandeh Amnieh, M. Hasanipanah, and L. Mohammad Khanli, "A new combination of artificial neural network and K-nearest neighbors models to predict blast- induced ground vibration and air-overpressure," Engineering with Computers, vol. 32, pp. 631–644, 2016.
9. E. Ghasemi, "Particle swarm optimization approach for forecasting backbreak induced by bench blasting," Neural Computing and Appli cations, vol. 28, pp. 1855–1862, 2017.
10. I. Ocak, "Interaction of longitudinal surface settlements for twin tunnels in shallow and soft soils: the case of Istanbul Metro," Environmental Earth Sciences, vol. 69, pp. 1673–1683, 2013.
11. D. J. Armaghani, M. Hajihassani, E. T. Mohamad, A. Marto, and S. Noo rani, "Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization," Arabian Journal of Geosciences, vol. 7, pp. 5383–5396, 2014.

12. D. Jahed Armaghani, M. Hasanipanah, and E. Tonnizam Mo hamad, “A combination of the ICA-ANN model to predict air-overpressure resulting from blasting,” Engineering with Computers, vol. 32, pp. 155–171, 2016.