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Ground Settlement Estimation in HDD: Lessons from Empirical, Analytical, Numerical, and Machine Learning Models

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ABSTRACT

Horizontal directional drilling (HDD) can induce ground settlement that poses a threat to roads, railways, and buried utilities. This study reviews and compares four approaches for estimating ground settlement: empirical, analytical, numerical, and machine learning methods. Eight representative studies are evaluated, encompassing clay, sand, layered ground, HDD, pipe jacking, and shield tunnelling. Each study is assessed using six criteria: (1) closeness to measured settlement, (2) number of input parameters, (3) overall complexity, (4) time required for calculation, (5) principal strengths, and (6) key methodological limitations. Evidence from published field measurements indicates that empirical formulas can reproduce settlement behaviour within the soils and project conditions for which they were calibrated, but their validity outside those conditions may be limited or uncertain. Analytical methods provide explicit relationships among ground loss, soil properties, geometry, and settlement-trough behaviour, but rely on idealized assumptions regarding soil behaviour, geometry, and boundary conditions. Finite-element and machine learning models demonstrated strong agreement with measurements in studies that included field validation. However, direct accuracy rankings among the reviewed approaches cannot be made reliably because the methods were applied to different projects and evaluated using different datasets and performance metrics. The study concludes that no single method is universally optimal. Instead, a combined strategy is recommended: simple empirical or geometry-based formulas may be used for preliminary HDD screening, while calibrated analytical or numerical models are more appropriate for critical crossings with strict settlement limits. Machine learning methods may provide additional predictive capability when sufficient high-quality, project-specific monitoring data are available.

INTRODUCTION

Existing infrastructures may be impractical or difficult to relocate, while new underground pipelines still need to be installed to provide essential services such as water supply to citizens. To make it feasible while minimizing surface disruption, the Horizontal Directional Drilling (HDD) method has been proposed. HDD is the trenchless installation method for pipelines beneath existing infrastructures such as roads, rivers, or buildings. A small-diameter borehole is drilled along a projected curved path controlled by a machine from the surface, and afterwards a product pipe is pulled into position. Several reaming passes then enlarge the borehole, and the soil cuttings are transported to the surface.

Additionally, throughout the process, a drilling fluid is circulated to support the created borehole and control pressures. Still, the ground settlement induced by HDD has become an increasing concern as urban environments have expanded. Facilities located above the projected bore alignment could be damaged by significant underground soil loss. Although surface disruption is minimal compared with open-cut excavation, ground movements such as heave or settlement remain crucial considerations. For this reason, estimating the magnitude of ground settlement has become an important aspect of trenchless construction.

Engineers have introduced several approaches to estimate settlement induced by HDD, including empirical, analytical, and numerical methods. In recent years, artificial intelligence (AI)-driven techniques such as machine learning have also been investigated for ground settlement prediction. The empirical method, the oldest one, uses field data, either directly or indirectly, to derive regression equations. Another method is analytical. This approach is a first-principles method that derives relationships from mechanical principles under idealized conditions: geometry, material behavior, and boundary conditions.

Furthermore, numerical methods use software-based models to estimate settlement under complex conditions, such as multiple adjacent pipelines, several soil layers, or complex HDD geometries. This literature review paper analyses the methods mentioned earlier. During the analysis, the strengths and limitations of the methods were identified and presented in a clear and concise manner. The objective of this study is to compare empirical, analytical, numerical, and machine learning approaches for ground settlement estimation and evaluate how their respective strengths, limitations, and requirements may apply to Horizontal Directional Drilling (HDD), while presenting the comparison in an accessible way for high school students and other early-stage researchers.

METHODOLOGY

The study used a comparative narrative literature review to examine empirical, analytical, numerical, and machine learning methods for estimating ground settlement in Horizontal Directional Drilling (HDD) and closely related trenchless construction. Candidate studies were identified primarily through Google Scholar, using combinations and variations of terms related to *HDD, horizontal directional drilling, ground settlement, surface settlement prediction, empirical settlement methods, analytical settlement methods, finite-element modeling, PLAXIS, machine learning, and shield tunneling settlement*. An exact count of papers considered was not recorded because the search was conducted as a focused literature review rather than through a formal screening protocol. To provide a balanced comparison across four estimation approaches, two studies were selected for each category.

For the comparative analysis, no predefined publication-date restriction was imposed, as the review aimed to encompass both foundational and recent studies relevant to the four estimation methodologies. Studies were included if the paper: (1) examined HDD or a closely related trenchless construction technique; (2) involved the estimation of ground settlement; and (3) demonstrated an explicit computational approach. Ultimately, eight studies were included: two empirical, two analytical, two numerical, and two machine learning studies.

The selected studies were then compared according to the six criteria: (1) closeness of the predictions to measured settlement or observed settlement behavior, (2) number of required input parameters, (3) overall complexity, (4) calculation time, (5) specific strengths and capabilities, and (6) methodological requirements or constraints associated with the computation process. Based on these criteria, comparison tables were prepared to summarize the characteristics, strengths, limitations, and available validation evidence for the reviewed studies.

The qualitative ratings used in Table 1B were assigned comparatively across the reviewed studies. Input parameters were assessed based on the number and types of parameters and the project-specific data required; overall complexity was assessed based on the volume of requirements such as the mathematical difficulty of the method, the amount of model setup required, the need for specialized software, and any data-processing or model-training requirements for estimation process in each method; and calculation time was assessed based on the amount of setup and computation described or implied by the method to obtain prediction. Thus, the ratings such as Very Low, Low, Medium, and High, or Very Fast, Fast, and Medium represent relative classifications within the eight reviewed studies.

LITERATURE REVIEW

The empirical method is one of the oldest approaches and uses field data to derive relationships or regression equations through which ground settlement can be approximated. This method has been applied extensively in shield tunneling studies. Although shield tunneling and pipe-jacking differ from HDD in their excavation procedures, geometry, and support systems, these trenchless methods can all cause ground loss or settlement; thus, relevant studies on tunneling and pipe-jacking can provide transferable knowledge for HDD settlement analysis. For instance, R.J. Mair, R.N. Taylor, and A. Bracegirdle (1993) employed a Gaussian representation of the settlement trough based on earlier work by Peck (1969, as cited in Mair et al., 1993). Under an approximate constant-volume assumption for clay tunneling, the volume of the settlement trough was related to the volume of ground loss. Mair et al. then fitted empirical relationships using field measurements and centrifuge model data. The resulting empirical relationships contain fitted numerical coefficients, as shown below:

$$\frac{S_{\max}}{a} = \frac{1.25V_L}{0.175 + 0.325\left(1 - \frac{z}{z_0}\right)} \cdot \frac{a}{z_0}.$$

$$K = \frac{0.175 + 0.325\left(1 - \frac{z}{z_0}\right)}{1 - \frac{z}{z_0}}.$$

Additionally, Mair et al. (1993) referred to earlier relationships for settlement prediction proposed by O'Reilly & New (1982, as cited in Mair et al., 1993), Rankin (1988, as cited in Mair et al., 1993), Peck (1969, as cited in Mair et al., 1993), and Clough & Schmidt (1980, as cited in Mair et al., 1993). The field and centrifuge data showed that the predicted settlement profiles generally agreed with the measured behavior of clay above the tunnels. However, the width of the settlement trough became wider at deeper subsurface depths than predicted. As Mair et al. note, the cause of this inconsistency is the use of the constant K=0.5, a value commonly applied to surface settlement in clay. Based on these observations, Mair et al. have introduced a depth-dependent relationships for the trough-width parameter and maximum settlement.

As a second example of the empirical method, the work done by Fei Wang, Linchang Miao, Xiaoming Yang, Yan-Jun Du, and Fa-Yun Liang (2016) was chosen because it involves a specific method usage for settlement estimation and shield tunneling in sand. This paper was released after R. J. Mair et al. (1993) and addresses some gaps arising from previous works. Building on the Mair et al. (1993) and earlier studies by Atkinson and Potts (1977, as cited in Wang et al., 2016) framework and Nakai et al. (1997, as cited in Wang et al., 2016), Hsiung et al. (2008, as cited in Wang et al., 2016), Jiang et al. (2008, as cited in Wang et al., 2016), Lee (2009, as cited in Wang et al., 2016), laboratory, and field studies, Wang et al. propose a volume-ratio parameter, $R_V = V_S / V_L$, and a depth-dependent trough-width parameter, K(z). Their result demonstrated that, in sand, the volume of the settlement trough is not necessarily equal to the volume of ground loss and changes with depth.

Another approach is the analytical method in which settlement prediction formulas are derived from mathematical relationships and simplified representations of soil behavior and geometry. For these formulas to be applied, several assumptions are usually required. For instance, the study conducted by Matthew Wallin, Kathryn Wallin, and David Bennett (2008) on the analysis and mitigation of settlement risks in new trenchless installations illustrated an analytical approach for estimating maximum ground settlement in trenchless installations. Wallin et al. represented the surface settlement trough as an idealized symmetrical profile and used straight influence lines extending from the bore to the ground surface to estimate lateral extent of settlement and forming an angle of (45° - φ/2) with the horizontal, where φ is the soil friction angle. Such an example of the use of simple geometry and trigonometry can be observed in the calculation of the settlement's width, as shown below:

$$w = \frac{d_b}{2} + \left(h_c + \frac{d_b}{2}\right)\tan\left(45^\circ - \frac{\varphi}{2}\right),$$
$$\beta = 45^\circ - \frac{\varphi}{2}.$$

Width of settlement trough, *w*, can be found by multiplying the tan β by the length of the adjacent side of the triangle $h_c + d_b/2$, where h_c is the depth of clearance above the borehole and d_b is a bore diameter, which gives us only the part of the width, since the angle is taken from the distance half of the d_b. Thus, to find the total width, the other half of d_b is added.

Wallin et al. (2008) related the maximum settlement at the bore centreline to the settlement volume per unit bore length and the effective trough half-width:

$$\Delta h_{CL} = \frac{V_s}{w}.$$

In the formula above, V_S represents settlement volume per unit bore length and therefore has units of area, $\frac{m^3}{m} = m^2$. Dividing V_S by *w*, which has units of meters, outputs the maximum centerline settlement, Δh_{CL}, in metres.

The second analytical method to predict ground movement in a tunnel built in clay was developed by Loganathan and Poulos (1998). They use parameters in their calculation that were created theoretically. One example is the gap parameter, g, originally proposed by Lee et al. (1992, as cited in Loganathan & Poulos, 1998). It is the combination of the planned geometric gap, 3-dimensional ground movement associated with stress relief next to the tunnel face, and additional construction-related movement:

$$g = G_p + U_{3D} + \omega.$$

Here, G_P is the planned geometric gap, U_{3D} represents three-dimensional ground movement near the tunnel face, and ω represents additional movement caused by construction effects.

Moreover, Loganathan and Poulos sketched a similar illustration of the tunnel in 2D format, where the ground deformation pattern was idealized with prescribed percentages of ground loss at different depths, and the soil is assumed to be uniform and behave elastically. Still, it gives a cogent analytical link between the shape of the settlement trough and ground loss.

One of the other alternatives, the numerical method, is a computer-based approach to a particular solution. Usually, it is used to solve complex (multivariable) problems via software programs. As an example, the study by Asif Ahmed, Md Azijul Islam, Md Zahangir Alam, and Hashmi S. Quazi (2023) was chosen because it employed a clear numerical modelling estimation method, computation of the ground settlement, and a direct application to Horizontal Directional Drilling (HDD). Ahmed et al. (2023) utilized PLAXIS2D to model ground settlement induced by HDD. The project's site was located on six different types of soil. Therefore, for a more accurate result, all six soil types should be considered as their distinct full set of soil parameters influences ground settlement, which played an important role in determining ground settlement in their study. Ahmed et al. outlined that analytical methods may be restricted to simplifying assumptions and boundary conditions, whereas numerical methods can represent layered soils and more complex geometries. To represent the stability analysis of the stress distribution in soil, Ahmed et al. demonstrated it with 15-node triangles that reflected the variation of settlement and stress. With this approach in calculating the ground settlement, the numerical method was compared to the empirical method. Eventually, both showed approximately similar results, but differed in particular moments.

Nevertheless, Ahmed et al. tested which parameter affects surface settlement the most by utilizing PLAXIS2D, and there were 4 different variables: friction angle, cohesion, modulus of elasticity, and pipe/boring geometry. They found that soil strength parameters, such as the friction angle, φ, and cohesion index, c, influenced the settlement value the most.

As a second study incorporating a numerical approach, the study by Binbin Xu, Runlai Yang, Hao Dai, Zhichao Dong, and Yongxing Zhang (2024) was selected because it utilized numerical modelling to investigate how HDD pilot holes used as pretreatment for rectangular pipe-jacking construction affected ground settlement beneath existing light-rail line. The same finite-element modelling was employed here as it was in the Ahmed et al. surface settlement induced by HDD study. In the study by Binbin Xu et al., a two-dimensional computer model of the ground with six soil and rock layers was illustrated, using the Mohr-Coulomb model and typical unit parameters. Eventually, they compared the resulting stress distribution and vertical displacement at the surface by varying the positions and diameters of the holes. Their numerical results estimated a maximum settlement of approximately 7.2 mm, compared with the measured value of approximately 8.1 mm, representing about 11% difference.

Apart from empirical, analytical, and numerical methods to estimate settlement, the machine learning method (ML) is considered to be one of the novel methods as artificial intelligence has developed. One of the papers involving the computation of ground settlement via ML in shield tunneling is Wentao Shang, Yan Li, Huanwei Wei, Youbao Qiu, Chaowei Chen & Xiangrong Gao (2024). Shang et al. used machine learning to analyze a limited dataset containing shield-operation, soil, and geometry parameters and to identify the variables that contributed most strongly to surface settlement. This is an example of a double-input deep neural network (D-DNN), an advanced technology that has output a longitudinal surface settlement profile along the tunnel alignment.

A second example of an ML method is an artificial neural network (ANN). It was employed by Ilies Ayari and Yacine Derbal (2025) in their study. Specifically, the ANN was trained on a dataset comprising 442 samples from the Algiers Metro. The data includes shield parameters such as penetration rate, face pressure, thrust, grout volume, and ground-loss indices, with cover depth and ground information. The output at each monitoring point was the maximum surface settlement. After training, the ANN achieved R^2 values above 0.92 and RMSE below 4.2 mm.

RESULTS

Table 1A summarises method types, applications, and evidence validation; Table 1B compares input requirements, complexity, and computation time; Table 1C presents the principal strengths and constraints; and Table 2 summarises the reported closeness to measured settlement.

Table 1A. Method, application, and validation evidence

Method (Authors, year)	Method type and main application/soil	Match with reality (settlement)
Mair et al. (1993) subsurface settlements in clay	Method type: Empirical (Gaussian trough) Main application/soil: Shield tunnelling in London Clay; surface and subsurface settlement	Qualitative agreement with field and centrifuge measurements; no overall percentage error was reported
Wang et al. (2016) volume and settlement in sand	Method type: Empirical (Gaussian + volume ratio) Main application/soil: Shield tunnelling in sand	Predicted trends were compared with laboratory and published field data; no overall percentage error reported.
Wallin et al. (2008) settlement risk for trenchless installations	Method type: Analytical (geometry-based) Main application/soil: HDD and microtunnelling; general soils (uses ϕ)	Low: No quantified field-validation result was reported; the predicted settlement depends strongly on the assumed proportion of annular volume converted into settlement volume.
Loganathan & Poulos (1998) analytical prediction in clays	Method type: Analytical (elastic solution) Main application/soil: Circular tunnels in soft to stiff clays	The approach was weighed against five tunnel case histories in clay; authors reported generally good agreement between predicted and observed movements.

Method (Authors, year)	Method type and main application/soil	Match with reality (settlement)
Ahmed et al. surface settlement induced by HDD under highway	Method type: Numerical (FE, PLAXIS 2D) Main application/soil: HDD beneath road/highway in layered soil	Not assessable from field data: The study compared empirical and numerical predictions. However, no corresponding field-measured settlement was reported. The empirical method gave S_{max} ≈7.3 mm; PLAXIS model gave S_{max} ≈4.6 mm (same order of magnitude, noticeable difference; no direct field monitoring)
Xu et al. (2024) HDD pilot holes & pipe jacking under light rail	Method type: Numerical (FE, 2D) Main application/soil: HDD pilot holes and rectangular pipe jacking in layered rock/soil under a light-rail line	High: best layout gives predicted S_{max} ≈7.2 mm vs measured ≈8.1 mm (≈11% difference); meets 10 mm safety limit
D-DNN (twin metro tunnels)	Method type: machine learning Main application/soil: Twin shield tunnels; longitudinal surface settlement	High: on its own site: higher R2 and much lower error than a simple DNN; fits measured longitudinal settlement curves well
ANN (Algiers Metro)	Method type: machine learning Main application/soil: Metro tunnel; maximum surface settlement.	High within the study dataset: R^2 >0.92 and RMSE <4.2 mm for S_{max}.

Table 1B. Input requirements, complexity, and computation time

Method (Authors, year)	No. of input parameters / input requirements	Overall complexity	Time to compute
Mair et al. (1993) subsurface settlements in clay	Low: Restricted to their London clay data set. Tunnel depth, tunnel radius, volume loss, trough-width factor K(z).	Medium: simple Gaussian formulas, use of collected data, and construction of a regression line.	Fast: spreadsheet or calculator.

Method (Authors, year)	**No. of input parameters / input requirements**	**Overall complexity**	**Time to compute**
Wang et al. (2016) volume and settlement in sand	Medium: Restricted to their sand data set, but captures that the settlement trough volume changes with depth and differs from tunnel volume loss. Tunnel geometry, depth, volume loss, depth-dependent K(z), volume-ratio $R_V(z)$.	Medium: more parameters than Mair, but uses simple algebraic formulas.	Fast: spreadsheet usage.
Wallin et al. (2008) settlement risk for trenchless installations	Very Low: Only variables are present. Bore and pipe diameters, clearance above bore, soil friction angle ϕ, assumed ratio $\frac{Vs}{Va}$.	Low: simple geometry and volume balance; feasible and easy to use.	Very Fast: hand or Excel.
Loganathan & Poulos (1998) analytical prediction in clays	Medium: Tunnel radius and depth, soil shear modulus and Poisson's ratio, gap parameter g (ground loss), surcharge (if any).	Medium: closed-form elastic solutions and gap concept; more maths than empirical methods.	Low: once implemented, formulas run quickly; some setup time.
Ahmed et al. surface settlement induced by HDD under highway	High: Soil layers (γ, E, ν, c, ϕ for each), HDD geometry, boundary conditions, mesh settings.	High: needs mesh, model building, Mohr-Coulomb soil model, staged construction.	High: each run takes a lot of time; a parametric study takes even more time.
Xu et al. (2024) HDD pilot holes & pipe jacking under light rail	High: Properties for six layers (γ, E, ν, c, ϕ), pilot-hole geometry, train/road loads, boundary and mesh settings.	High: full FE model with Mohr–Coulomb soil/rock and mesh refinement.	High: model building + mesh sensitivity + multiple layouts.

Method (Authors, year)	No. of input parameters / input requirements	Overall complexity	Time to compute
D-DNN (twin metro tunnels)	High initially: Numerous shield-operation, soil, and geometric inputs were considered then reduced by feature selection.	High: needs data processing, network design, and training.	Medium: training can be slow initially; once trained, predictions are fast.
ANN (Algiers Metro)	High: Several shield parameters (penetration rate, face pressure, thrust, grout volume, etc.) + simple ground data.	High: needs data pre-processing and ANN training.	Medium: Training takes time; once trained, prediction is instant.

Table 1C. Main strengths and key constraints/requirements

Method (Authors, year)	Main strengths	Key constraints/requirements
Mair et al. (1993) subsurface settlements in clay	Simple, fast, widely used in tunnelling and HDD; gives settlement at any depth; based on real data.	Calibrated for stiff clay only; assumes Gaussian shape and volume of settlement equals volume of ground loss; HDD effects (drilling fluid, overcut) only included indirectly via volume loss. Ignores underlying soil mechanics and theories. Highly depends on the collected data.
Wang et al. (2016) volume and settlement in sand	Extends the Mair framework to sand; introduces volume-ratio Rv and depth-dependent K(z); more realistic for sandy ground.	Based on limited centrifuge and field data, assumes a Gaussian trough; not directly calibrated for HDD or other soils. A small amount of explanation on the theories and mechanics of soil. Highly depends on the collected data.

Method (Authors, year)	Main strengths	Key constraints/requirements
Wallin et al. (2008) settlement risk for trenchless installations	Directly uses HDD variables (overcut, annulus, pipe size); very simple; good for quick risk screening/teaching.	Multiple assumptions: assumes a symmetric trough and homogeneous soil; settlement volume taken as a fraction of annulus volume without strong data; no detailed subsurface profile. Reality differs from the demonstrated analytical work.
Loganathan & Poulos (1998) analytical prediction in clays	Mechanically cogent; gives full vertical and horizontal displacement fields; links gap/ground loss to settlement shape.	Assumes uniform, elastic clay and plane strain; calibrated for tunnels, not HDD; needs an estimate of gap/ground loss, which can be uncertain. Fails to consider several other parameters that might have affected a surface settlement.
Ahmed et al. surface settlement induced by HDD under highway	Can model layered soil and accurately predict the behavior of ground movement and illustrate it precisely on a computer; can study the influence of ϕ, c, E; shows which soil parameters affect settlement most. Applicable to complex geometry soils.	Requires many soil parameters and software; 2D only; no direct field validation in the paper; drilling-fluid effects are simplified. Require a computer understanding to run the software with accuracy. It can be expensive to use.
Xu et al. (2024) HDD pilot holes & pipe jacking under light rail	Can optimise HDD hole layout under strict settlement limits; directly linked to monitored field case; includes layered ground and surface loads. Applicable to complex geometry soils.	2D plane-strain simplification of a 3D problem; needs detailed stratigraphy and parameters; drilling-fluid physics still simplified. Depends on the person's knowledge of the software. Expensive.

Method (Authors, year)	**Main strengths**	**Key constraints/requirements**
D-DNN (twin metro tunnels)	Captures very complex relations between many parameters and settlement; excellent fit to training/validation data.	Black-box model; no explicit formula; strongly site-specific; transfer to another project requires external validation and may require model retraining; needs a sufficiently large, high-quality monitoring database.
ANN (Algiers Metro)	Simple structure; good prediction of S_{max} for the studied metro; shows potential of ML to replace hand-tuned empirical models.	Also, a black box with no simple formula, cannot be applied directly to HDD or other sites without retraining; depends on a large local monitoring database.

Table 2. Closeness to real settlement reported in the reviewed studies

Method	**Basis of comparison**	**Closeness to real settlement**
Mair et al. (1993) empirical, clay	Predicted vs measured troughs in London Clay.	Authors state "good agreement" in plots, but there is no numerical error or % given.
Wang et al. (2016) empirical, sand	Predicted vs laboratory and published field data in sand.	The curves match well in the visuals, indicating qualitative agreement, but no explicit measurement or % error is reported.
Wallin et al. (2008) HDD / trenchless analytical	Only worked example calculations.	No monitoring data given, so reality-closeness is not quantified.
Loganathan & Poulos (1998) analytical	Several clay tunnels (Heathrow, Thunder Bay, etc.).	Authors state "good agreement" between predicted and measured profiles across five clay tunnel case histories; no single percentage error was reported.
Ahmed et al. PLAXIS HDD under highway	Same HDD case: empirical vs numerical.	Empirical S_{max} ≈7.3 mm, numerical S_{max} ≈4.6 mm; thus, numerical ≈35–40% lower than empirical; no field-measured data.

Method	Basis of comparison	Closeness to real settlement
Xu et al. (2024) FE, HDD pilot holes & pipe jacking	Numerical result vs monitored settlement under light rail.	Case 2: predicted 7.2 mm, measured 8.1 mm, thus, difference ≈11%, within 10 mm safety limit.
D-DNN (twin tunnels)	Model-to-model comparison (S-DNN vs D-DNN). Values do not represent direct comparison with the field-measured settlement.	Compared with the single-input DNN, the D-DNN increased average R^2 by 27.85% and reduced average MAE by 53.2%.
ANN (Algiers Metro)	Predicted vs measured S_{max} at monitoring points.	Reported R^2 >0.92 and RMSE <4.2 mm; no single % error reported.

DISCUSSION

Results will be discussed here, based on tables from analyses of various studies on ground settlement in shield tunneling and HDD. Regarding the empirical method of estimation, some might think that it is an unreliable source since it focuses only on the data obtained. This may be true, depending on the quality of the data; however, this method is usually validated by correlation with previous experience. Thus, the proposed regression lines are restricted to the location or type of soil in the study.

Furthermore, empirical methods are simple to employ since only the data need to be analyzed and trends identified between them, unlike numerical and machine learning methods, where it is necessary to thoroughly analyze, identify relationships between variables, and obtain ample soil details to determine the desired parameter precisely. From the comparison tables, it can be seen that, generally, the empirical approach agrees with the observed settlement within the conditions under which it was restricted. However, since the authors Mair et al. and Wang et al. did not state an overall percentage error, the closeness of the predictions to measured settlement cannot be quantified directly. Since the empirical methods are derived based on observed data, they can reproduce settlement behaviour within the conditions represented by those data. It had some discrepancies, though. The particular reason for this circumstance was the assumptions made in determining the maximum depth of settlement, such as assuming a constant trough width parameter, which does not completely reflect the real behaviour of the soil. Overall, the empirical method can provide useful predictions under the conditions for which it was calibrated, and it involves relatively simple calculations.

Analytical approaches rely on idealized assumptions; Thus, their accuracy depends on how closely applied assumptions represent the actual soil conditions and construction process. In detail, it usually requires a lot of assumptions (settlement forms a Gaussian curve, Volume of settlement is equal to volume of ground loss) to be made and needs calibration with real fieldwork data to be valid. However, Loganathan and Poulos (1998) assessed their method against five tunnel case studies in clay and reported generally good agreement between predicted and measured ground movements. Even though the geometry-like picture seems too perfect for the process to happen like that with different types of soils beneath the ground, Loganathan and Poulos (1998)'s computed values were pretty accurate since they addressed the limitation faced in Mair et al.'s study, where it was stated that the width should not be constant for every depth. This type of ideal case illustration, though, enables the formation of closed-form equations, despite the irregular ground movements in reality. In most cases, when there is a huge amount of considerations necessary to be made, the analytical method may not be suitable. Still, in some of the cases, the analytical process can be sufficient.

Numerical methods have demonstrated a close correlation to the observed ground settlement, especially in Xu et al. (2024) study. In the study conducted by Ahmed et al. (2023), the empirical and numerical methods predicted maximum settlements of approximately 7.3 mm and 4.6 mm, respectively. However, since no corresponding field-measured settlement was reported, the comparison cannot assess which method was closer to reality. Still, another study showed a cogent correlation to observed surface settlement. The reason for this precision and accuracy in this method is that it incorporates as many details as possible to match the real behavior of soil and ground movements, and uses complex software programs such as PLAXIS2D, ABAQUS, etc., which are considered reliable tools for approximations.

To sum up, the numerical method has advantages when it comes to modeling complex geometries that cannot be done with bare hands. Thus, the numerical methods can represent layered soils, complex geometries, and different construction conditions in greater depth than simplified empirical or analytical models. Yet, their accuracy is sensitive to the input parameters, modeling assumptions, boundary conditions, and field validation. Additionally, creating such models consumes a lot of time, depends on the quality of the data, and requires sufficient knowledge of software for the result to be precise.

Ultimately, the modern approach that has emerged only in recent years – machine learning method. According to the results, this method shows agreement with measured field settlement on the specific projects and datasets on which the models were trained. The studies also demonstrate how, in this case, a more sophisticated ML approach can increase prediction accuracy with added architecture to the baseline model. In the Algiers Metro study, the artificial neural network (ANN) achieved an $R^2 > 0.9$ and a root-mean-square error of approximately 4 mm for the maximum surface settlement at monitoring points, indicating strong agreement with the measured settlement. In the twin tunneling study, the D-DNN enlarged the effective data volume by more than 1.5 times in comparison with the single-input DNN (S-DNN), increased the average R^2 by 27.85%, and reduced the average MAE by 53.2%. These improvements reflect the better performance of the D-DNN relative to the S-DNN baseline; they are not a direct percentage comparison with the field-measured settlement.

CONCLUSION

In this study, several methods of estimation (empirical, analytical, numerical, and machine learning) were compared based on the literature available that explicitly employs one of these methods to calculate ground settlement and are closely relevant to Horizontal Directional Drilling (HDD). Common criteria were considered in the analysis, including closeness to real behavior, number of required parameters, overall complexity, time needed for a calculation, specific strengths, and unavoidable constraints. The review of empirical methods (for example, Mair et al. for London Clay and Wang et al. for sand) indicates that this method is relatively simple to employ and accurate in the calculation of the ground settlement within the soil conditions and projects on which they were calibrated. However, these regression trends are tied to their original data sets and may not be applicable to other studies.

The results of the analytical method demonstrated that they are more tied to soil mechanics' concepts and theories. In some cases, they provide an accurate estimation, close to the real one, and in others, they oversimplify results from the data.

Numerical finite-element models, as illustrated by Ahmed et al. and Xu et al., are the most flexible of the classical approaches. They can include layered ground, realistic boundary conditions, and complex geometries such as HDD pilot holes, rectangular pipe jacking under existing railways, and other existing infrastructures on the surface. But, at the same time these methods require a considerable amount of time, quantity of input elements, and precise use of the software to achieve results, not deviating too much from the reality.

The analyzed machine learning works yielded strong results within their project datasets. In contrast, as sites, outputs, and evaluation metrics vary between studies, machine learning performance cannot be ranked directly against other methods. Machine learning methods are most appropriate in the presence of sufficient representative and high-quality monitoring data.

For Horizontal Directional Drilling (HDD) applications shield-tunnelling studies can still offer proof on ground loss, settlement behavior, and data-driven estimation relevant to HDD, even though it differs from HDD in construction processes. Generally, a combined strategy appears most reasonable: empirical or simplified geometry-based methods can be used for preliminary screening, while calibrated analytical or numerical models are more suitable for critical projects with strict settlement limits. Machine learning models may provide extra support when sufficient data are available.

LIMITATIONS

This study has several limitations that should be recognized when interpreting the results. This literature review was based entirely on secondary data, and only on a limited number of representative methods from each group (empirical, analytical, numerical and machine learning) on HDD ground settlement estimation methods analysis due to a lack of access to academic journals and papers. Therefore, the results do not cover all existing approaches in the literature. The majority of the papers do not report full numerical details, such as explicit percentage errors or complete sets of soil parameters. Thus, some of the criteria had to be assessed qualitatively or visually, especially in the comparison table, which used relative rating classifications such as Very Low, Low, Medium, and High, or Very Fast, Fast, and Medium rather than universal thresholds. Moreover, this analysis relied on shield tunneling studies in some cases as the most closely related method to HDD for trenchless installations. Nevertheless, the analysis of different computational methods was not conducted on the same case study, which means that the performance of each method may vary across projects. Moreover, no pictures could be added to illustrate the examples for better comprehension due to policies regarding authors' rights in the Lumiere Research Program. These limitations suggest that the conclusions should be viewed as indicative trends rather than as definitive rankings. Additionally, multiple foundational studies were accessed through secondary citations identified in the reviewed papers rather than consulted directly, which might limit the depth of interpretation of those original papers.

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