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Soil information model for prediction the soil properties characteristics

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Abstract. The soil properties characteristics are the object of the current study. Determination of the soil properties characteristics is a complex and responsible engineering and geological task. Reliability of engineering construction and its cost depend on the quality of solution of this task. The article presents the results of the study of the possibility of predicting the soil properties characteristics on the example of determining the sand deformation modulus. Based on the analysis of previous studies of correlation between the soil properties characteristics, the list of independent soil properties characteristics was determined: soil genesis, static normal stress, granulometric composition, initial density and humidity of the soil sample. The main disadvantages of existing methods of predicting the soil properties characteristics were identified. The possibility of using artificial neural network for predicting the soil properties characteristics was determined. The soil deformation modulus was selected as a response (dependent variable). The presence of not only numerical but also classification features among the independent characteristics did not allow predicting the soil properties characteristics within the framework of the classical regression model. A soil information model, based on an artificial neural network, was used to solve this problem because not only continuous quantitative but also discrete classification parameters (genesis) can be used among the independent parameters of the soil information model. Laboratory studies of 655 samples of alluvial sand of the Irtysh River floodplain were performed to confirm the possibility of using the soil information model. 5895 data vectors were obtained, including information on independent and response parameters. A detailed study of two granulometric compositions demonstrated limited possibilities for using known statistical methods for determining the soil properties characteristics. In 9 out of 20 cases, the results of the studies did not follow a normal distribution. The use of the soil information model allowed to solve this problem – the absolute percent error in determining the deformation modulus did not exceed 12.55 % (mean – 5.05 %), the coefficient of determination R^2 was at least 0.83 for unloaded sand samples, and at least 0.94 for loaded ones, for all datasets – 0.97. The performed studies confirmed the prospects of using the soil information model for predicting soil properties based on its known characteristics, which reduced the cost of engineering and geological surveys while ensuring the required accuracy of determining the soil characteristics.

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1. Introduction

Characteristics of soil properties are used to classify soils, describe their condition and reaction to external influences of various nature. Determination of the characteristics of the physical and mechanical soils properties is a complex engineering task. At the present time both theoretical and practical scientists continue to solve this task, despite the rich scientific and practical experience of engineering and geological surveys, laboratory determination and subsequent statistical processing of the obtained data. The reason for this is not only the variety of characteristics of various soil properties: physical, mechanical, chemical, etc., used for engineering purposes, but also the soils variability, caused by the stochastic nature of their genesis. Evidently, this diversity of characteristics, combined with soil variability, requires a large number of samples to ensure the required reliability of the results of the characteristics determination. Since after laboratory studies, as a rule, the studied samples have a broken structure and are unsuitable for reuse as samples, the task of determining the required soil characteristics ceases to be only an engineering task. There is an economic aspect – the need to increase research expenses.

To solve the problem, the author proposes a method, which reduces the number of samples needed and the number of studies for determining and predicting the soil properties characteristics. It is based on both correlations between characteristics and modern digital technologies. Thus, the soil properties characteristics are the object of the current study. A new method for predicting the soil properties characteristics is the subject of the study.

1.1. Correlations between the Soil Properties Characteristics

The solution to the problem of reducing the number of definitions of the soil properties characteristics is seen in the search for a correlation between the characteristics of various soil properties. Thus, the correlation between the characteristics of various soil properties will allow predicting the required characteristics based on the characteristics already studied.

In 1925, K. Terzaghi was one of the first to point out the possibility of a correlation between the characteristics of soil properties [1]. He systematically identified the factors “on which the occurrence and course of phenomena depend, with special consideration for the two elements of deformation and time”. He established the influence of packing density on the friction coefficient in sand, water content and previous loading history in loams and clays as well. Analyzing the experience accumulated by his predecessors, K. Terzaghi assigned the leading role in the science of soils to the knowledge of the soil physical properties, suggesting “to rely more on the physical properties of the soil”. He wrote about “the need to build the structural mechanics of the soil based on the physics of the soil”. He stated that “knowledge of the physical properties of the soil gives us the opportunity to establish a causal relationship between physical causes and technical action in soil construction (landslide, sediment, failure of the foundation, etc.) and when we are not able to present this relationship completely in mathematical form”.

In 1941, N.N. Maslov formulated the basic law of the relationship between the soil properties and their formation conditions (genesis). This law establishes that rocks that are identical in their composition, genesis, and occurrence conditions and have undergone the same subsequent changes have the same engineering and geological properties [2].

In 1955, A.K. Birulya reported on the influence of the soil granulometric composition (grain-size distribution, GSD), the composition of its colloidal part, density, humidity and temperature on the soil strength [3].

In 1967, G. Müller pointed out the influence of the processes of soil particles weathering and transportation, that is, the conditions of their formation, on their shape, which determines, in turn, the nature of the mutual adhesion of particles in the soil, the mechanism of their contact [4].

In 1971, M.N. Gol'dshtejn noted “the complexity and diversity of natural conditions that determine the soils mechanical properties” [5]. The author reported on the need “for engineering and geological studies to constantly reveal the relationship between the properties of soils and the conditions of their formation and occurrence, and the material accumulated in this way by survey organizations should be systematically generalized by specialists in the field of engineering geology”. It was also noted that “the physical and mechanical properties of those sedimentary rocks that are classified as non-rock soils are determined, firstly, by the relative content of particles of various minerals and the size of these particles, and secondly, by the properties of substances that fill the pores of the soil”.

In 1975, F.J. Pettijohn reported on the influence of the formation (genesis), sand mineral composition, and the shape of its particles on the classification characteristics of sandy soil [6].

In 1981, L.M. Arya and J.F. Paris presented a model to predict the moisture characteristic of a soil from its particle-size distribution, bulk density, and particle density parameters [7]. Their model predictions for several soil materials show close agreement with the experimental data.

B.J. Cosby et al. reported, “the name used for the soil in the description relates to the principal soil type and, in general, is based on particle size or the presence of organic material. The soil name thus provides valuable qualitative information concerning the physical and mechanical properties of the material” [8].

In 1989, V.A. Korolev established on the basis of thermodynamics the basic laws of changes in the phase composition and phase ratios of dispersed soils, including during compressive compaction of soils, allowing to predict changes in a number of soil properties during these processes [9].

In 1990, E.C. Drumm et al. reported about the need to take into account the influence of the magnitude of cyclic deviator stress to characterize the soil subgrade and related soil-index properties and the moduli obtained from unconfined compression tests, to resilient modulus M_R [10].

In 1994, D. Li and E.T. Selig developed a method that takes into account the influence of soil physical state, moisture content, stress state, and soil type on M_R of compacted fine-grained subgrade soils [11].

C.R.I. Clayton et al. reported on the influence of the soil particles size on its physical and mechanical properties and on the classification of soils based on their quantitative characteristics [12].

In 1996, S.F. Brown having studied pavement failure mechanisms reported about the influence of soil moisture and loading regime on the soil M_R [13].

L.M. Arya et al. used particle-size data and form of soil particle in their investigation to estimate the soil-water characteristic [14].

In 2002, M.D. Fredlund et al. used information on GSD and the volume-mass properties of a soil for developing a procedure for estimating the soil-water characteristic curve [15]. They also reported about potential to use GSD as a basis for estimating soil behavior [16].

In 2004, N. Khoury and M.M. Zaman studied the influence of moisture changes on the M_R of subgrade soils. They reported that M_R-moisture content relationships for clayey soil exhibit a hysteretic behavior due to wetting and drying. A similar behavior was observed for sandy soil. The clayey soil was more susceptible than the sandy soil to moisture variation. They reported that changes in M_R values and suction were influenced by the initial moisture content [17].

P.S.K. Ooi et al. suggested using data on stress state, soil type, soil structure, and the soil physical state to improve the model for predicting the soil M_R [18].

In their studies, X. Yu et al. demonstrated that “the parameters affecting the shear strength therefore depend on the relative density, gradation, particle strength, particle size and shape, and degree of saturation of the specimen” [19].

In their experimental researches, J.H.S. Kung et al. demonstrated that the stress state, moisture content, and soil suction influenced the M_R and the plastic strain [20]. Unsaturated subgrade M_R reduces with increasing deviator stress and decreasing matric suction. The subgrade plastic strain increases as the deviator stress increases and the matric suction decreases.

T. Wichtmann and Th. Triantafyllidis presented “a study of the influence of GSD curve on the small strain shear modulus G_{max} of quartz sand with sub-angular grain shape” [21]. The article reported on the need to take into account the shape of soil particles when modeling the effect of granulometric composition on its characteristics.

H. Nowamooz et al. carried out an experimental study of the repeated load response of a compacted clayey natural sand at different water contents. It has been proven that there is a strong link between the variation of the bearing capacity of low traffic pavement and the water content of the unbound layers [22].

In 2012, A. Ward reported that “particle size is a fundamental property of any sediment, soil or dust deposit. It influences a variety of other soil properties” such as natural isotope abundance, hydraulic properties, transport properties, thermal properties, reactive properties, and electrical properties [23].

N. Khoury et al. conducted several studies to develop relationships between the M_R of subgrade soils and moisture conditions [24]. They reported that the relationships between M_R and the moisture content exhibit a hysteretic behavior similar to the soil-water characteristic curve; specimens subjected to drying exhibited higher M_R values than specimens subjected to wetting. M_R values on the drying-wetting-drying path are different from the corresponding values on the wetting-drying path.

In 2013, T. Enomoto et al. reported about correlation between increasing of soil grain size and uniformity coefficient and G_{vhd} shear modulus by dynamic measurement and G_{vhs} shear modulus converted from E_{vs} quasi-elastic vertical Young's modulus by static measurement [25].

In 2013, A. Shaqlaih et al. reported about modeling of the M_R correlation with routine properties of subgrade soils and state of stress for pavement design application [26].

C.W.W. Ng et al. investigated using a suction-controlled cyclic triaxial apparatus M_R values of a subgrade soil under various stress and suction conditions. They reported that the measured M_R is highly dependent on the stress state [27].

In 2014, Z. Han and S.K. Vanapalli proposed equations for predicting the M_R of granular materials by using soil-water characteristic curve and GSD [28].

In 2014, N. Lu and M. Kaya reported that for soils, in addition to their well-known dependence on stress, elastic moduli (Young's modulus and shear modulus) depend on volumetric water content and/or matric suction, particularly for silty and clayey soils [29].

In 2015, G.G. Boldyrev and M.V. Malyshev noted that the physico-mechanical soils properties are the result of a complex and long-term interaction of physico-chemical conditions of rock formation, conditions of their occurrence, tectonic processes, regional geological processes associated with the action of gravity of water, gases, temperature fluctuations, biological factors. It was noted that the aerometric definitions data can be useful for assessing the physical and mechanical soils properties as well [30]. It was also noted that in the first approximation, to solve the problems of designing foundations, the angle of internal friction of loose soils can be determined from the correlation of data by statistical probing, relative density, and classification indicators. The shape of the particles, especially sandy soils, affects their strength properties. The soils genesis most often determines their basic physical and mechanical properties.

In 2015, V.A. Korolev and S. Chzhan reported the results of their studies of the effect of the granulometric composition of a mixture of various sizes fractions on the indicators of physical and physico-mechanical properties – density, porosity, internal friction angle, etc. As factors of influence, they considered GSD, addition density, mineral composition, humidity [31]. They found that for sandy and coarse-grained soils, the leading factors are GSD, particle shape and density of soil composition.

I. Ishibashi and H. Hazarika reported on the influence of GSD of the soil and its origin on its properties: “since soil is an assemblage of particles, interlocking of those particles and their contact mechanism – in particular, for larger particles – determines many important mechanical properties of soils such as strength, rigidity, permeability, and compaction” [32]. They reported about soil characteristics correlation: from GSD curve, several key parameters can be obtained, such as the effective grain size (D_{10}), the mean grain size (D_{50}), the coefficient of uniformity (C_u), and the coefficient of gradation (C_g). Those parameters will be used in soil classification practices and will be correlated with many engineering properties of soils such as in compaction, permeability, etc.

A.V. Mel’nikov and G.G. Boldyrev proposed to include the consistency index I_L from the cone penetration tests (CPT) data for clay soils as an additional argument in the correlation equations for clay soils and the specific sleeve resistance f_s – for sands to increase the determination accuracy of deformation modulus E [33]. They reported about decreasing the determination accuracy of the E with increasing content of grainy and clayey fractions in soils as well.

In 2016, A.V. Gruzin et al. proposed a method for regulating the deformation properties of an incoherent dispersed soil based on the granulometric composition [34].

M. Goudarzy et al. conducted “a series of resonant column and compression wave velocity tests simultaneously on dense and loose specimens containing 0, 10, 20, 30, 40 and 50 gravimetric percentages of fine particles to measure the small strain moduli (G_{max}, M_{max} and E_{max}) of the mixtures. Mixture samples were prepared by the moist tamping method and subjected to isotropic confining pressure levels of 50, 100, 150 and 200 kPa” [35]. The authors found that “the accuracy of the predicted maximum stiffness depends on the accuracy of the equivalent granular void ratio”.

At the same time, T. Enomoto reported after series of drained triaxial compression tests that quasi-elastic vertical Young's moduli, E_{vs}, measured statically, were generally independent of maximum and mean particle diameters and the effects of fines content and particle angularity on the E_{vs} values were not clear [36].

W.-T. Hong et al. reported on the particle size influence on the soil-water characteristic curve during cyclic tests [37].

In his experiments, M.A. Khasawneh showed a slight increase in M_R values with an increase in confining pressure and a noteworthy decrease in M_R accompanied by an increase in deviatoric stress [38]. Also based on the independent samples t-test analysis, it was revealed that soil type and water content caused statistically significant difference in M_R values.

G.I. López researched grain size analysis methods and noted that granulometry is a basic analytical technique. Several sediment, soil, or material properties are directly influenced by the size of its particles as well as their shape (form, roundness, and surface texture of the grains) and fabric (grain-to-grain interrelation and grain orientation), such as texture and appearance, density, porosity, and permeability [39].

I. Dyka et al. presented the results of laboratory tests that verify the correlation between the grain-size characteristics of non-cohesive soils and the value of the dynamic shear modulus [40].

F.F. Badhon and Md.A. Islam reported about studying the gradation effect on shear strength of sand with various water contents [41]. They performed several direct shear tests on reconstituted sand samples having different GSD (well graded (WG), gap graded (GG), and uniform graded (UG)) with varying water content of 15 % and 25 %. They have established that higher shear strength was obtained for GG soil as compared with the WG and UG.

The research of P.H. Thinh et al. was focused on the correlation between compression index C_c and other properties of the marine dark grey lean clay layer. Their research results showed that the correlation between C_c and liquid limit is the tightest [42].

Y. Sun et al. reported about development of the new grading parameter that considered the size distribution of the entire aggregates to capture the grading-dependence of the shear stiffness of heterogeneous granular aggregates [43]. The grading parameter was found by them to increase with decreasing coefficient of uniformity and median particle size where higher shear stiffness was observed. It was also found that the proposed grading parameter exhibited an improved power-law correlation with the material constants from Hardin's stiffness formula compared with the traditional grading parameter, the coefficient of uniformity.

In their monograph, G.G. Boldyrev and I.H. Idrisov reported numerous empirical dependencies that allow determining the elastic shear modulus G_{max} of coarse – grained and sandy soils based on data on the granulometric composition, particle shape, porosity coefficient, and initial stress conditions [44].

Y. Yao et al. used correlations between the physical properties of subgrade soils including the percentage passing through the No. 200 sieve (0.075 mm), plasticity index, liquid limit, dry density, and the regression coefficients of the new model [45].

In 2019, A.V. Gruzin proposed a method for regulating the characteristics of physical and mechanical properties of dispersed unconnected soil by granulometric synthesis [46].

In their research, B. Ghorbani et al. used the accurate determination of M_R of pavement subgrade soils with its dependence on several influential factors, such as soil physical properties, applied stress conditions, and environmental conditions [47].

The report of C. Mendoza et al. presented the compression behavior of Bogotá's diatomaceous soils. The investigations results have found several practical relationships for secondary consolidation, compressibility index, yield point, initial void ratio, and soil structure. These results show the importance of geological history for soil structure and secondary consolidation [48].

D. Watanabe et al. reported about GSD influence on degree of size segregation in granular flow simulations [49]. They confirmed that the inherent degree of the size segregation clearly affects the run-out distance.

The previously reviewed articles analysis shows that the characteristics of the soil physical properties are most often used as independent variables (often called "predictors" or "features"), such as GSD, density, humidity, and genesis (formation). Many authors reported about the need to take into account influence of the soil stress state as well. Numerous authors most often considered as dependent variables ("responses") the characteristics of the soils mechanical properties, namely the resilient modulus M_R and shear modulus G. Evidently, such a choice is due to the practical relevance of these characteristics.

1.2. Methods for Predicting the Soil Properties Characteristics

There are many methods for developing correlation models for predicting the soil properties characteristics: analytical, empirical, statistical, etc. At present time, regression models (RMs) have become widely used. Such models make it possible to locally solve the problems of predicting the required soil characteristics by using independent predictors. The development of scientific basis for processing the results of partial definitions of the characteristics of the object under study is the one reason for the widespread RMs using. The second reason is the practical confirmation of the adequacy of the results of forecasting performed using RMs. According to the Interstate standard GOST 24026-80, regression analysis model is the dependence of the response on quantitative factors and errors of observation of the response; regression analysis is a statistical method of analyzing and processing experimental data when only quantitative factors affect the response, based on a combination of the apparatus of the least squares method and the technique of statistical hypothesis testing. It is evident that the engineering and geological conditions uniqueness of each new construction site and the stochastic nature of the soils formation each time give rise to the need to develop new adequate RMs. The scientific approach to planning experimental studies of the soils characteristics allows us to comprehensively solve the problems of both the stochastic nature of the soil properties and the need to ensure the required accuracy of determining the desired characteristic. Many articles are devoted to problems related to the experimental studies planning, the RMs development and their practical use for predicting the characteristics of the soils properties.

In his monograph, C.R. Hicks in detail described the basic concepts of experimental design, from the problem formulation to the results interpretation [50]. Author analyzed the advantages and disadvantages of various models and pointed out the need to establish a list of independent variables that can influence the dependent variables. The same principles and approaches are followed by the authors of [51]. The methods presented by them make it possible to develop a RM for a wide range of cases encountered in practice, including those related to the need for optimization. In [8] the authors reported about possibility to construct models that are based on continuous spatial variation in physical soil properties (such as sand or clay content) which provide even better simulations of soil moisture. In [10] the authors described and demonstrated two statistical models for 11 soils from throughout the state of Tennessee. Authors reported both models provide a good characterization of the response for the soils investigated. In [11] the authors proposed to quantify the soil physical state effect by combinations of two equations relating M_R to moisture content. In [21] the authors reported the proposed correlations predict quite well most of the small strain shear modulus G_{max}-values reported in the literature for sands with a sub-angular grain shape. In [26] the authors developed statistical models to correlate M_R with routine properties of subgrade soils and state of stress. In 2014, a series of uniaxial compression tests were conducted on various compacted soils under varying volumetric water content [29]. The authors of this research proposed a simple power law to describe the dependence of Elastic moduli (Young's modulus and shear modulus) on volumetric water content for all types of soils. In [31] the authors have considered questions of modeling of sandy soils with specified physical and physical-mechanical properties using triangular diagrams represented by modified Feret triangles. X. Luo et al. reported in [52] about development and verification moisture-sensitive and stress-dependent mechanistic-empirical models to predict soil M_R. In [42] the authors revised Terzaghi and Peck formula and proposed a new formula most suitable for the correlation between compression index and liquid limit of the soil layer for geotechnical design in Vietnam and Cambodia. In [45] the authors reported about the development of RM to predict M_R based on subgrade soil physical properties. Authors stated that M_R can be predicted much more easily with physical parameters of subgrade soils rather than conducting triaxial tests. In 2019, A.V. Gruzin proposed computer program modeling the properties of a three-component system using the Gibbs method [53]. The program is designed to calculate using one of the four proposed regression equations and visualize the obtained numerical values of the characteristics of the physical and mechanical properties of dispersed noncohesive soil by constructing a 3D-surface as a function of three independent predictors (fractions of dispersed noncohesive soil). The author reported in [54] a percent error of less than 13.6 % for the physical properties characteristics and less than 2.6 % for the mechanical properties characteristics when predicting using the proposed model, based on Gibbs–Roseboom method. In [47] the authors used the accurate determination of M_R of pavement subgrade soils with its dependence on several influential factors, such as soil physical properties, applied stress conditions, and environmental conditions.

The main RM advantage is an ease of understanding and using for predicting an algebraic equation based on basic statistical principles. At the same time there are some disadvantages of RM, such as certain difficulties in working with categorical variables, in correctly describing nonlinear correlations, in decreasing of the RMs reliability with the variables number increasing and some others.

1.3. Predicting Models based on the Artificial Neural Networks

Many modern studies have shown that the use of the artificial neural networks (ANNs) successfully solves such RM problems as working with categorical (classification) variables.

An attempt at a systematic approach to the analysis of the prospects for the use of ANNs in civil engineering is undertaken by I. Flood and N.A. Kartam in [55, 56]. The authors reported neural networks advantage compared to conventional digital computing techniques, and procedural and symbolic processing. They noted that designing a successful approach for applying ANNs to a specific problem requires experience and imagination as well. E. Tutumluer and R.W. Meier attempted to train ANN constitutive model for computing the M_R of gravels as a function of stress state and various material properties [57]. They reported the pitfalls inherent in the indiscriminate application of ANNs to numerical modeling problems. M. Shahin et al. analyzed many reports on the use of ANNs in engineering fields. They reported that ANNs have been applied successfully for many geotechnical engineering areas, one of is the prediction of soil properties and behavior [58]. In 2004, they investigated four data division methods used for training ANNs. It was reported that the statistical properties of the data in the training, testing, and validation sets need to be taken into account to ensure that optimal model performance is achieved [59]. Y.M.A. Hashash et al. have developed self-learning in engineering simulation analysis framework, which extracts relevant soil behavior using boundary measurements of load and displacement, facilitated by use of ANN constitutive model [60]. M. Zaman et al. developed four different feedforward-type ANN models: linear network, general regression NN, radial basis function network, and multilayer perceptrons network (MLPN) [61]. In each of these models, the input layer consists of seven nodes, one node for each of the independent variables. The output layer consists of only one node – M_R. The MLPN model with two hidden layers was found to be the best model for the present development and evaluation data sets. In 2012, M.D. Nazzal and O. Tatari developed the ANN models resulted in subgrade M_R predictions with significantly higher accuracy than those estimated using RMs with the same input variables [62]. They reported the use of genetic algorithms in developing the ANN models resulted in enhancing their prediction significantly.

S.-H. Kim et al. developed of an ANN model to estimate subgrade M_R [63]. Authors reported the stress state and physical properties on resilient behavior of subgrade soils were successfully correlated with developed ANN model. H. Tao et al. used back propagation (BP) neural networks algorithm to simulate parameter model of soil GSD based on soil particle analysis tests, and used to simulate the function relationship between soil volumetric water content and matrix suction, which were calculated based on Arya–Paris model [64]. Authors reported about applicability and reliability of their proposed method. To achieve the specified accuracy, the authors used two hidden layer nodes of BP neural networks algorithm. S. Saha et al. developed ANN models to predict the coefficients of a stress- and moisture-dependent M_R model for plastic and nonplastic soils [65]. The developed ANN models consist of three layers, seven input variables, ten hidden neurons, and one output variable. Their models are the three-layered ANNs. The authors did not recommend ANNs for use as a prediction tool for the values that are out of the range of training dataset. The authors reported a good prediction accuracy of the developed models results in better estimation of the M_R of base materials – the R^2 value between the measured and predicted validation M_R values was 0.8. In 2022, I.V. Ofrikhter et al. reported on the successful use of ANN in solving the problem of predicting soil properties [66]. As a result of their research, obtained ANN predicts the angle of friction and specific cohesion of clay soil with reasonable accuracy. The authors proposed the topology of the ANN and carried out the comparison of the estimation accuracy with the existing equations.

ANNs using has become a new stage in the development of RMs for predicting the soils properties characteristics. A review of recent publications confirms this fact.

1.4. Soil Information Model

The previously performed studies analysis allows us to conclude about the complexity of the task of the soil physical and mechanical properties characteristics predicting. When predicting responses (dependent variables), there are different approaches in the selection of influence factors (independent variables). Some of authors mention both quantitative and classification factors as well [2, 6, 30]. Evidently, for correct statistical processing of laboratory results, it is necessary to establish type of probability distribution. Statistical processing of laboratory research results, as a rule, includes the search for and exclusion from consideration of the so-called “gross errors”. Previously performed studies do not provide an explanation for such a phenomenon as “gross errors” during the research data statistical processing. Obviously, the reason for the presence of so-called “gross errors” is ignoring the influence of certain factors (features) that are not included in the developed RM. The solution of this problem is seen in the development and use of a soil information model based on RM developed using ANNs, since, according to the Interstate standard GOST 24026-80, the classical regression analysis model is the dependence of the response (dependent variables) on continuous quantitative factors (independent variables) and response observation errors (error terms).

Soil information model (SIM) is an object-oriented electronic (virtual) parametric model that digitally represents the characteristics of the soil (or its separated components) in the form of a set of information-rich elements (features, parameters, characteristics – continuous quantitative and discrete classification) for various external conditions.

It should be noted that in addition to solving the problem of predicting the soil properties characteristics, an important advantage of SIM is its open architecture. This makes it possible to develop SIM by adding to it both new research results and new influence factors (independent variables). It is expected that such SIM will allow predicting soil characteristics using fewer soil samples in comparison with existing methods. This means that SIM using will lead to a reduction of material expenses and waste of time when conducting engineering and geological surveys while maintaining the reliability and necessary accuracy of the obtained characteristics.

Thus, the main purpose of the current study is to develop a method for predicting the soil properties characteristics based on the correlation between the various soil properties characteristics – continuous quantitative and discrete classification and on ANN using.

To achieve this goal, the following tasks were solved:

- the list of independent soil properties characteristics was determined, the main disadvantages of existing methods for predicting the soil properties characteristics were identified, the ANN using possibility to predict the soil properties characteristics was determined, based on the analysis of previously performed studies;
- the laboratory studies of soil samples were carried out in order to determine the values of independent characteristics of soil properties and the necessary information database for ANN training and testing was formed;
- SIM, based on a trained ANN, was developed for predicting the soil properties characteristics and the accuracy of predicting the soil properties characteristics on its base was evaluated.

2. *Materials and Methods*

2.1. *Laboratory tests*

According to the Russian Code of Practice SP 22.13330.2016, the calculation of the engineering construction foundation for the second group of limit states (by deformation) using the deformation modulus E is always performed, with the exception of three trivial cases. Therefore, E is selected as a response (dependent variable) of the developed SIM. The availability of proven methods and certified laboratory equipment can reduce the risks of methodological and operational errors in determining E.

2.1.1. Experiment design

The minimum number of soil samples (≥ 6) was determined for each combination of the specified independent soil characteristics (variables, factors), according to the Russian Code of Practice SP 22.13330.2016. As independent soil characteristics, the following were selected: soil genesis, static normal stress σ, soil sample granulometric composition, its initial density ρ and moisture w. The test program developed in accordance with the Interstate standard GOST 12248.4-2020 is shown in Fig. 1.

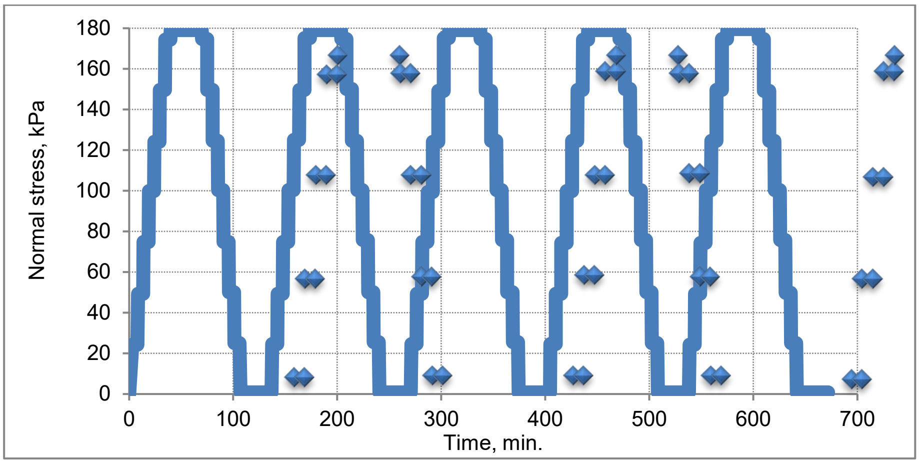


Figure 1. Program of the soil compressibility laboratory tests.

The maximum σ value is determined by the operating conditions for the bases of vertical steel tanks for storing oil and its refined products [67].Compression tests are cyclical in nature and consist of five stages. The number of loading stages shown in Fig. 1 is due to the need to study the effect of the soil initial density ρ on the deformation modulus E.

Statistical processing of the results of laboratory studies for each combination of the specified independent soil characteristics and for each static normal stress σ stage was performed in accordance with the methods presented in [50, 51]. Statistical processing of the results of laboratory soil samples tests included the following main stages: verification of the laboratory data to follow normal distribution, exclusion of “gross errors” of measurement results, determination of the normative soil characteristic value and its root-mean-square deviation (RMSD).

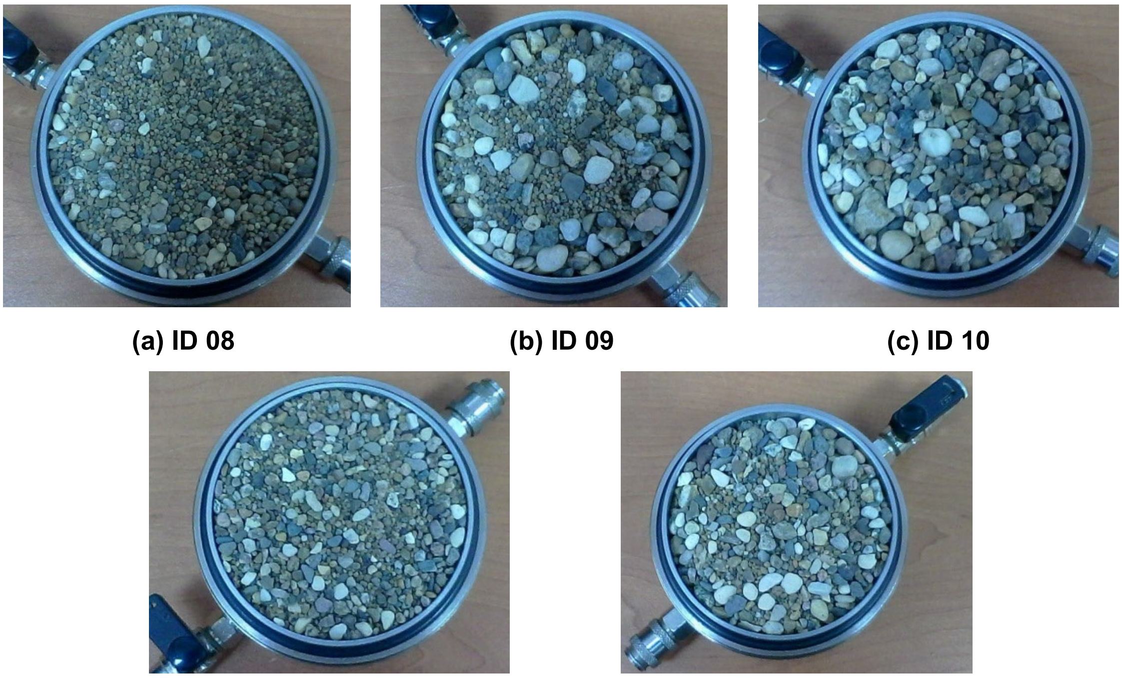
2.1.2. Materials

Sand was chosen as a dispersed incoherent soul because it is necessary to correctly change the soil GSD and to provide the required and controlled values of its independent characteristics for all test samples. Alluvial sand of the Irtysh River floodplain was used for laboratory studies. The initial dry sand was separated by the sieve method into grain size fractions, which were then used to prepare test-samples (Table 1) for laboratory studies in accordance with the research program. The laboratory equipment used for compression tests limited the maximum particle size of the soil test samples. Therefore, fractions with a particle size of more than 10 mm were not used in the studies. The mass fraction of such particles in the original sand was less than 0.2 %.

Table 1. Sand test-samples used in the present study.

Sand sample ID	The soil mass fraction as a function of the sieve mesh size							Number of samples
	5.0 mm	2.0 mm	1.0 mm	0.5 mm	0.25 mm	0.1 mm	Pan	
01							1.0	35
02						1.0		45
03					1.0			30
04				1.0				65
05			1.0					50
06		1.0						35
07	1.0							130
08		0.5	0.5					30
09	0.5		0.5					40
10	0.5	0.5						40
11	0.34	0.33	0.33					105
12	0.2	0.4	0.4					50

Samples dimensions are 25 mm in height and 78 mm in diameter. Fig. 2 illustrates examples of sand test samples with different granulometric composition.



(a) ID 08 **(b) ID 09** **(c) ID 10**

(d) ID 11 **(e) ID 12**

Figure 2. Sand mix test samples.

The different mineralogical composition of the sand test-samples did not allow for the same values of the initial values of its density ρ. Therefore, the actual value of ρ was determined before each test. The results of determining ρ for various stages of cyclical compression tests are shown in Fig. 3 where ***ave*** is the arithmetic mean, ***s*** is RMSD, ***max*** is the maximum value ρ, ***min*** is the minimum value ρ. The values of the initial density ρ were in the range of 1.30–1.64 g/cm^3 as the measurements showed.

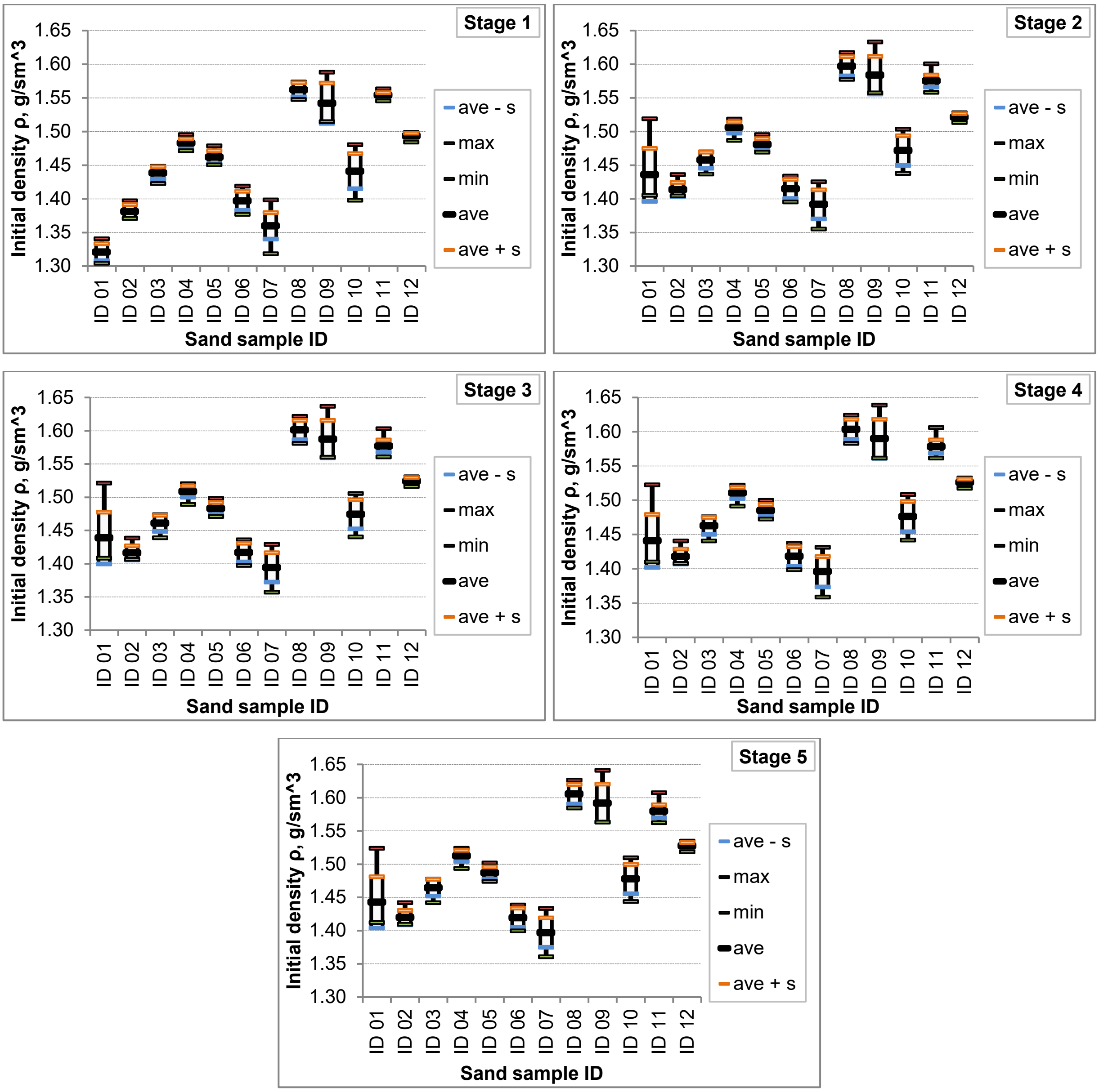


Figure 3. Samples initial density ρ.

In addition, taking into account the complex nature of the sand humidity w influence on its deformation properties [68], it was decided to limit the studies to air-dry sand, the humidity w of which was controlled before laboratory tests and was in the range 0.001÷0.0013.

2.1.3. Laboratory equipment

Fig. 4 illustrates universal automated ASIS test complex for conducting compressibility laboratory tests.

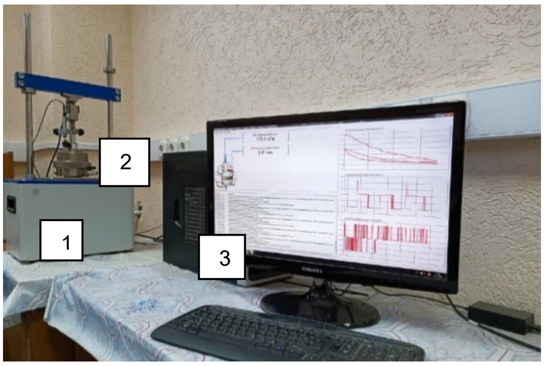


Figure 4. ASIS – equipment for soil compressibility laboratory tests.

The main elements of the ASIS are a loading device (1), a compression oedometer (2), specialized software for computer-based automation of the tests processes (3). The ASIS software regulates the amount and duration of soil sample loading in accordance with the compression test program shown in Fig. 1. The current time, the amount of soil sample loading, and the soil sample deformation are recorded during compressibility laboratory tests.

2.2. Soil Information Model

As it was noted earlier, the presence of not only numerical but also classification features among the independent variables does not allow predicting the soil properties characteristics within the framework of the classical RM. Sand formation (genesis), for example, is the one of such classification features. It is obvious that further research will also solve this problem since, at a minimum, the classification concept of the soil genesis should include the soil mineralogical composition, the particles shape, that is, characteristics having non-classification quantitative representation. But at this stage of investigations, such detail would obviously significantly complicate the planned research. Thus, since there are classification features among the independent variables, the prediction of the soil properties characteristics can be implemented using SIM based on ANN.

Previous studies review and analysis have shown that ANNs are widely used to solve engineering forecasting problems [55–66]. There are various software approaches for ANN implementation and subsequent modes of its development. The choice was made in favor of the "open source deep learning framework for Python – Keras" due to its simplicity, sufficient number of training materials and accessibility [69, 70]. Work with ANNs starts with its algorithm development. The ANN algorithm used in the research included the following stages of working with the source data: loading and subsequent separation of data into independent variables (features) and response, normalization of the source data, their random permutation and subsequent division into three groups – training, control-verification, and test datasets. The training dataset is needed to train ANN. The control and verification dataset are used for the current control of ANNs training. The test dataset is to evaluate the trained ANN. 655 sand samples were used in the studies, for which 5895 different measurements were performed. In accordance with the recommendations [69], 60 % of the data (3537 measurement results) were used for ANN training, 20 % (1179) – for its current verification, the remaining 20 % (1179) – for evaluation of the trained ANN. The next stage was the ANN model development. A sequential model consisting of 8 layers was used as ANN model: 12 neurons in the input layer, 64 neurons in the hidden layers, and 1 neuron in the output layer. ANN training is an important stage. "Supervised learning" was chosen from the existing methods of ANN training [69]. "Supervised learning" assumes that there is a target vector representing the desired output for each input data vector. Together they are called a training pair. This choice is due to the implementation simplicity and the operational ability to evaluate the results of trained ANNs. The model was trained for about 1200 epochs. As a loss function there was used mean squared error (MSE), widely used in regression analysis, which calculates the square of the difference between the predicted and target values [69]. Program control was carried out to prevent ANN overfitting (overtraining) during the ANN training process. At the final stage, the trained ANN was tested on a test dataset to assess the accuracy of response prediction.

3. Results and Discussion

3.1. Laboratory Studies

During laboratory studies, 655 soil samples were tested. 5895 data vectors were obtained, including independent variables (features) and response. The results of the laboratory studies is presented in Fig. 5.

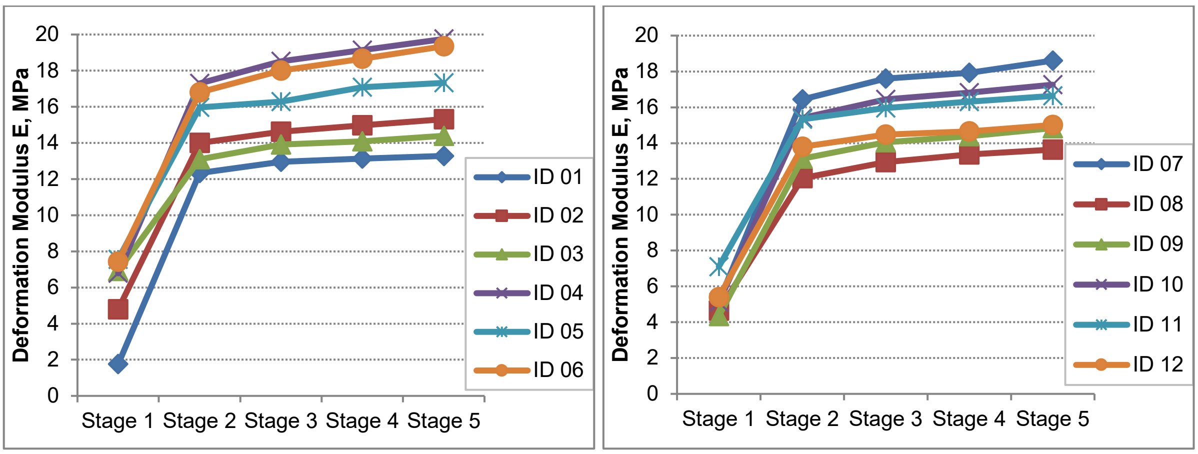


Figure 5. Soil samples deformation modulus E changing during compression tests.

Nonlinear nature of the change of the deformation modulus E of sand samples, depending on the number of stages of their loading, was established during the processing the compression tests results. Minimal changes of the deformation modulus E were observed for the sample ID 03. After the second stage of loading, the deformation modulus E of the sample ID 03 increased by 1.89 times (from 6.92 MPa to 13.10 MPa), after the third – by 1.06 times (from 13.10 MPa to 13.60 MPa), after the fourth – by 1.01 times (from 13.90 MPa to 14.08 MPa), after the fifth – by 1.02 times (from 14.08 MPa to 14.39 MPa). Thus, after five loading stages, the deformation modulus E of the sample ID 03 increased by 2.08 times. The maximum changes in the deformation modulus E were observed for the sample ID 01. After the second stage of loading, the deformation modulus E of the sample ID 01 increased by 7.05 times (from 1.75 MPa to 12.34 MPa), after the third – by 1.05 times (from 12.34 MPa to 12.95 MPa), after the fourth – by 1.01 times (from 12.95 MPa to 13.12 MPa), after the fifth – by 1.01 times (from 13.12 MPa up to 13.28 MPa). Thus, after five loading stages, the deformation modulus E of the sample ID 01 increased by 7.58 times. The performed studies have established the nonlinear nature of the influence of the granulometric composition on the deformation modulus E of sand.

The results of deformation modulus E determining for various stages of cyclic loading are shown in Fig. 6 where ***ave*** – arithmetic mean, ***s*** – standard deviation, ***max*** – maximum value, ***min*** – minimum value.

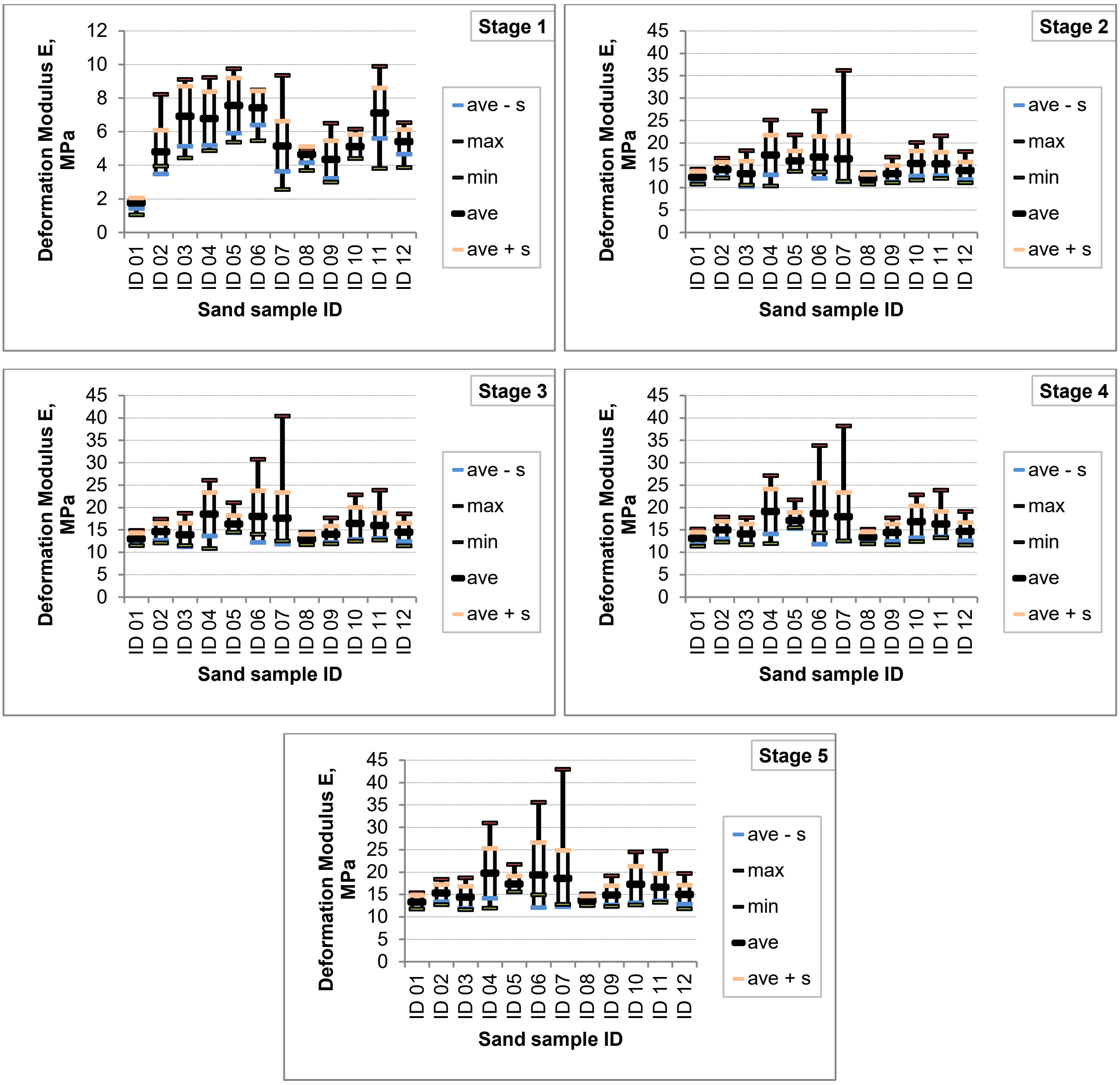


Figure 6. Soil composition influence on deformation modulus E.

As can be seen from the laboratory data, the minimum values of the coefficient of variation (CV) of the deformation modulus E for all loading stages were obtained for the sample ID 08 – from 0.0788 to 0.1025. The maximum CV values were obtained for samples ID 06 and ID 07 – from 0.2899 to 0.3765. At the same time, the minimum CV values of the initial density ρ were obtained for samples ID 11 and ID 12 – from 0.0023 to 0.0034. The maximum CV values were obtained for samples ID 01 and ID 09 – from 0.0194 to 0.0267 (Fig. 3). Thus, during the conducted studies there was not revealed a significant influence of the precision and repeatability of the determinations of the initial density values on the precision and repeatability of the determinations of the deformation modulus E. It was established that CV of the initial density ρ values is, as a rule, ten times less than the CV of the deformation modulus E. In the studied range of normal stress, there is established the linear nature of the influence of the soil sample initial density ρ on its deformation modulus E.

According to the Interstate standard GOST R 8.736-2011 for samples ID 07 and ID 11, there was verified the hypothesis that the results of independent testing of the initial density ρ and the deformation modulus E follow the normal probability distribution law. Initially, according to the Interstate standard GOST 20522-2012, for the samples ID 07, it was established that for all loading (normal stress) stages, the soil initial density ρ dataset is homogeneous (CV ≤ 0.15). At the same time, the soil deformation modulus E dataset for the first stage of loading is homogeneous (CV ≤ 0.3), for the other remaining loading stages it is inhomogeneous. For sample ID 07, 5 soil samples were excluded from 26 soil samples as having “gross errors”. After excluding “gross errors”, all the remaining datasets on their soil deformation modulus E and the initial density ρ were homogeneous. Table 2 presents the results of verifying the hypothesis that the results of independent testing of remaining 21 samples follow the normal probability distribution law at a significance level q over 5 %.

Table 2. Sand samples ID 07 and ID 11 testing results.

Sand sample ID	Soil characteristics	Stage	Initial number of samples	Allowed number of samples	Mean	s	Follows the normal distribution
ID 07	Initial density ρ	1	26	26	1.360	0.020	Yes
		2	26	25	1.393	0.022	No
		3	26	25	1.395	0.022	Yes
		4	26	23	1.399	0.022	No
		5	26	24	1.398	0.023	No
	Deformation modulus E	1	26	26	5.138	1.490	No
		2	26	25	15.652	3.199	No
		3	26	25	16.688	3.468	No
		4	26	23	16.319	2.376	No
		5	26	24	17.120	3.048	No
ID 11	Initial density ρ	1	21	21	1.555	0.004	No
		2	21	20	1.574	0.007	Yes
		3	21	19	1.575	0.007	Yes
		4	21	20	1.577	0.008	Yes
		5	21	20	1.578	0.008	Yes
	Deformation modulus E	1	21	21	7.100	1.503	Yes
		2	21	20	15.466	2.654	Yes
		3	21	19	15.675	2.214	Yes
		4	21	20	16.435	2.838	Yes
		5	21	20	16.777	3.058	Yes

The hypothesis that the remaining initial density ρ dataset follows the normal probability distribution law was confirmed only for the first and third normal stress stages. The hypothesis that the remaining deformation modulus E dataset follows the normal probability distribution law was not confirmed for any normal stress stage.

For the samples ID 11, it was established that for all normal stress stages, the soil initial density ρ dataset is homogeneous (CV ≤ 0.15). For all normal stress stages the soil deformation modulus E dataset is homogeneous (CV ≤ 0.3) as well. However, according to the Interstate standard GOST R 8.736-2011, 3 soil samples were excluded from 21 soil samples ID 11 as “gross errors”. Table 2 presents the results of verifying the hypothesis that the results of independent testing of remaining 18 samples follow the normal probability distribution law at a significance level q over 5 %. The hypothesis that the remaining initial density ρ dataset follows the normal probability distribution law was not confirmed only for the first normal stress stage. The hypothesis that the remaining deformation modulus E dataset follows the normal probability distribution law was confirmed for all normal stress stage.

Thus, the obtained research data demonstrate a limited possibility of using methods for processing measurement results based on the hypothesis that the measurement results follow the normal distribution for such characteristics of soil properties as the sand initial density ρ and its deformation modulus E. The impossibility of developing adequate regression models for these characteristics is an important consequence of this conclusion.

3.2. Prediction based on SIM

The developed SIM on the basis of a trained ANN made it possible accuracy evaluation of the soil deformation modulus E predicting. The remaining 20 % of the dataset (test array) – 1179 laboratory measurement results were used for this purpose. It should be particularly noted that **ALL** (5895, without any exceptions) measurement results of soil samples laboratory tests were used for the training, verification and testing purposes. The results of SIM testing are presented in Fig. 7. The test array contains data of different samples under different normal stress.

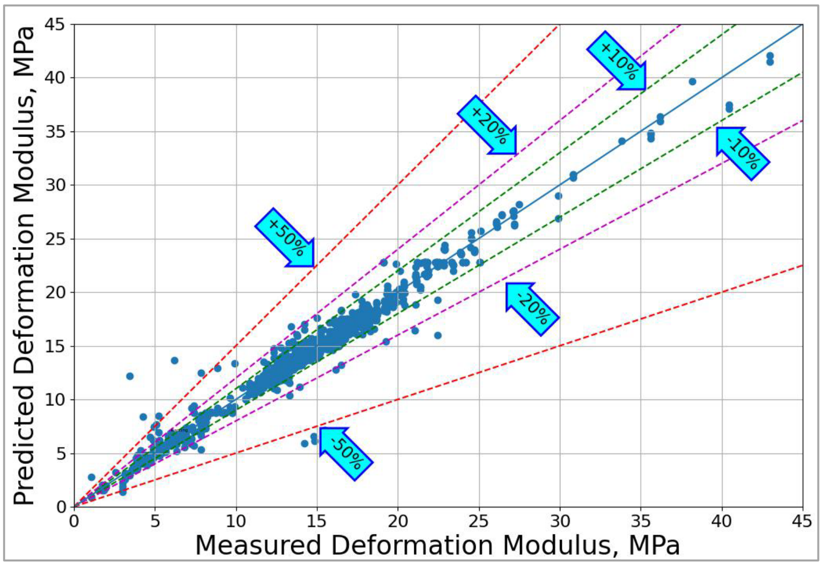
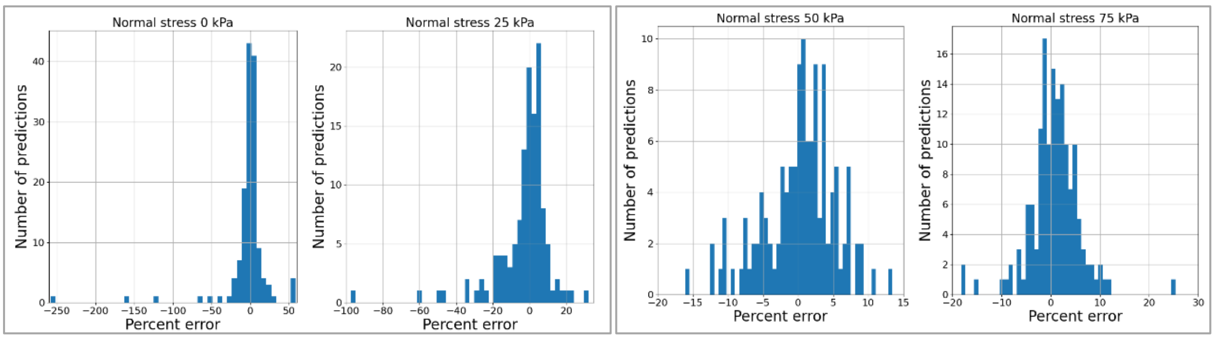


Figure 7. Prediction of the deformation modulus E using SIM.

The percent error (PE) is proposed to use as a characteristic for determination the accuracy predicting. The PE values for various normal stresses, which allow us to estimate the accuracy of deformation modulus E predicting using a SIM, are presented in Fig. 8.



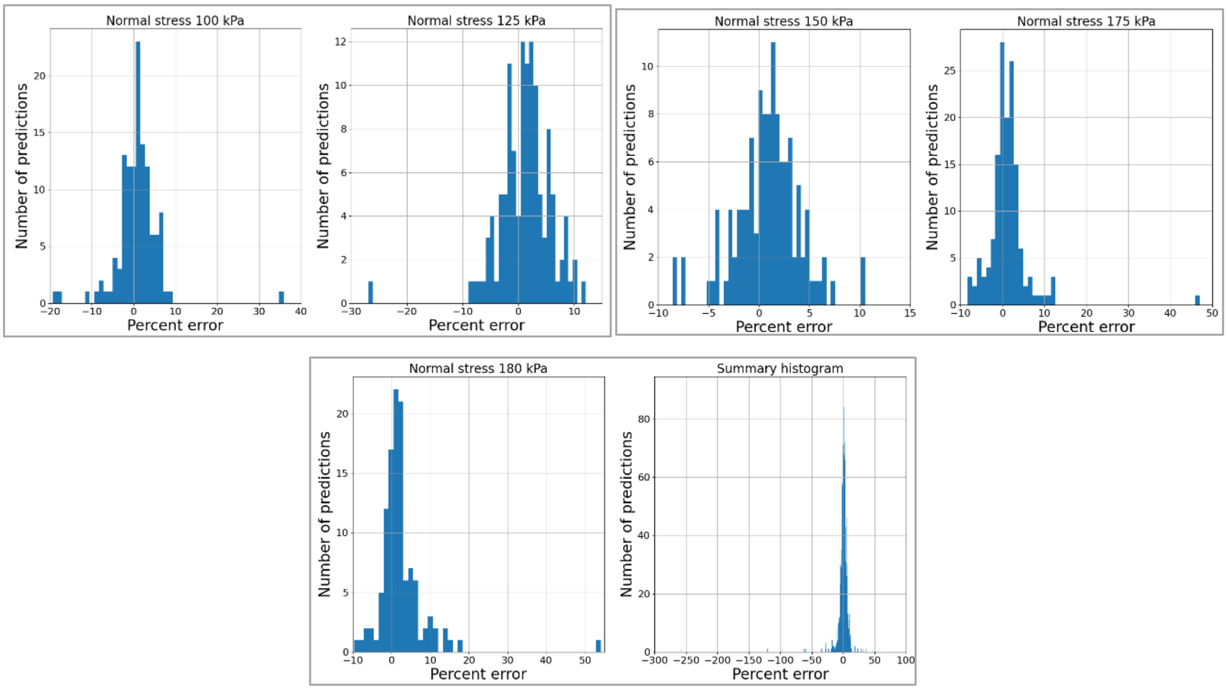


Figure 8. PE in predicting the deformation modulus E using SIM for various normal stress conditions of soil samples.

PE was in the range from –257.81 to 58.66 %, as can be seen from the data presented in Fig. 8. This maximum range (316.47 %) is for unloaded soil samples. For normal stress of 25 kPa, PE range is 129.56 %, for 50 kPa – 29.47 %, for 75 kPa – 43.61 %, for 100 kPa – 55.18 %, for 125 kPa – 39.02 %, for 150 kPa – 19.10 %, for 175 kPa – 55.31 %, for 180 kPa – 63.80 %. Fig. 9 shows the PE values for various normal stress conditions.

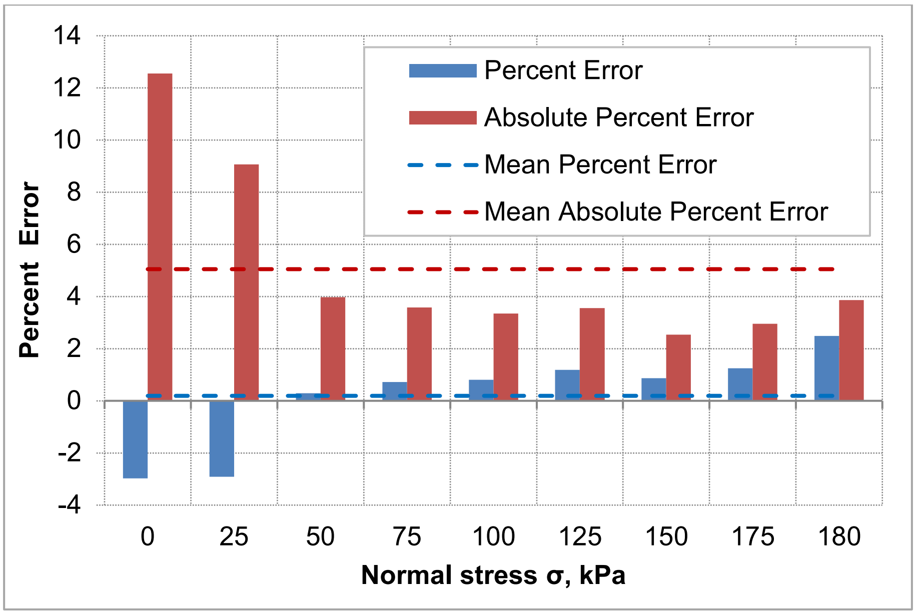


Figure 9. Prediction results accuracy.

The maximum absolute PE value (12.55 %) is for unloaded soil samples. The minimum absolute PE value (2.54 %) is for normal stress σ = 150 kPa. Mean absolute percent error (MAPE) is 5.05 %. The results of test array predicting using SIM are presented in Table 3.

Table 3. Results of the test array prediction.

Normal stress σ, kPa	Percent error δ, %				Coefficient of determination R^2
	Min	Max	Mean	Mean absolute	
0	–257.81	58.66	-2.97	12.55	0.8265
25	–97.46	32.10	-2.91	9.06	0.9403
50	–16.06	13.41	0.29	3.97	0.9810
75	–18.21	25.40	0.72	3.59	0.9902
100	–19.32	35.87	0.81	3.35	0.9873
125	–26.93	12.08	1.19	3.56	0.9910
150	–8.57	10.53	0.87	2.54	0.9931
175	–8.34	46.98	1.24	2.96	0.9942
180	–9.71	54.09	2.49	3.86	0.9913
For all dataset	–257.81	58.66	0.19	5.05	0.9684

Analysis of the values in Table 3 shows that the prediction accuracy characteristics (MAPE and coefficient of determination R^2) obtained on base SIM correspond to values of the same characteristics obtained by another researches [65, 66]. In current study the minimum value of coefficient of determination R^2 = 0.8265 is for unloaded soil samples (normal stress σ = 0 kPa), for normal stress σ = 25 kPa – 0.9403, for others – more than 0.98. For all dataset the coefficient of determination R^2 = 0.9684. The reason for the low coefficient of determination values is the greater and stochastic effect of the friction forces between the soil particles on the soil density for small values of normal stress (≤ 25 kPa).

4. Conclusions

The results of the soil properties characteristics prediction using SIM, the independent parameters of which are continuous quantitative and discrete classification features, are presented in the article. The following conclusions are drawn on the basis of laboratory studies outcomes:

1) the possibility of the soil deformation modulus prediction based on its genesis and physical properties characteristics is confirmed;
2) independent variables sufficient set – soil characteristics: genesis, normal stress, granulometric composition, initial density and humidity – has been confirmed to determine soil deformation modulus;
3) the possibility of SIM using based on a trained ANN to predict the soil properties characteristics, including cases when classical regression models using is impossible, has been confirmed;
4) the SIM using experience shows that small amounts of data (less than 10000 measurement results) for training ANN allow us to obtain satisfactory results in the soil properties characteristics predicting;
5) the SIM using allows to abandon the deformation modulus direct studies, and to determine it indirectly using SIM without losing the determination accuracy, minimizing material and time expenses.

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