Load Effect Impact on the Exploitation of Concrete Machine Foundations Used in the Gas and Oil Industry

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***Abstract*—Machine foundations is a critical topic in the gas and oil industry, which design and exploitation require extensive technical knowledge. Machine foundations are the constructions which are intended for mounting on it a specific type of machine. The foundation has to transfer dynamic and static load from machine to the ground. The primary difference between machine foundations and building foundations is that the machine foundations are a separate structure, even if they are inside the building. Failures of machine foundations can be very dangerous due to its carry loads from machines in operation. There is also an economic aspect because every break in the operation of industrial machines is expensive, especially in the gas and oil industry, where technological processes are complex and multi-stage. Repairs to concrete machine foundations are problematic, so the capability to predict what exactly affects failures seems extremely necessary. The failure of concrete machine foundations depends on many factors that are not fully understood. Modern achievements of science and technology, especially machine learning techniques may allow determining what affects the failure rate. This paper presents an analysis with the use of machine-learning techniques to predict in which way loads can affect the failure of foundations. This study examines whether and what relations exist between variables describing loads about the machine concrete failures occurrence. The analysis concerned some variables such as cross-section reinforcement amount, the grate load, measured concrete strength, motor short circuit moment load, the engine unit and rotor with shaft load, the pump unit and rotor with shaft load, the weight of the foundation, total load with foundation self-weight. The primary parameter of concern is the failure occurrence rate.**

***Index Terms*—concrete, data mining, failure occurrence prediction, machine concrete foundations, machine learning**

I. Introduction

Machine foundations are intended for mounting on its industrial machines, in case of gas and oil industry, these machines are related to the technological process of oil refining. These foundations are installed independently of the existing building structure and have to transfer static and dynamic loads from the machines in operation to the soil. Designing foundations for machines as separate structures originating in particular from the risk of transferring dynamic loads to the structure in which they are located in, also due to the dynamic loads mentioned these foundations are relatively often subjected to failure. It is also worth noting that each foundation is designed individually for a particular type of machine, which makes it difficult to evaluate them in a unified way. The primary material for such type is foundation is concrete. Determining what exactly affects the failure rate is problematic. The change can be brought by machine learning methods, which can help to find conclusions about the variables that characterize a given foundation and examine the relationship between them. This paper presents a study in which the machine learning techniques were used to examine the impact of loads on the failure rate of machine foundations.

II. Foundations for Industrial Machines and Machine Learning Techniques

A. Foundations for Industrial Machines

The issue of machine-foundation systems either design and maintenance is a complicated matter. Machine-foundations during its exploitation time must meet specific requirements considering reliability, safety, stability, and overall performance. The most important are the design process, construction conditions and interaction with soil. The primary function of the machine foundations is a transfer of static and dynamic loads from the machine to the soil [1]. Example of machine foundation is presented in Fig. 1.

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Figure 1. Foundation for an industrial machine [source: sigma-projekt.pl]

B. Machine Learning Techniques

Machine learning in recent times has gained much recognition in many areas, as science branch, it is a field of artificial intelligence dealing with the study of algorithms and systems that improve their performance along with the gained experience, which refers to information from the learning dataset used to teach the algorithm. Machine learning algorithms detect dependencies in data and create information based on them. Machine learning algorithms are often used in situations where obtaining the knowledge would be difficult by conventional methods. This particularly applies to the processing of large datasets. Teaching the algorithm, in this case, can be considered as the substantiation of the complex algorithm. One of the most widely used machine learning methods is Artificial Neural Networks (ANN). ANN consists of many neurons, which can be described as an information converter. The neurons in ANN behave as organic neurons imitating in this way a human brain. In theory, there are at least three layers of ANN, called the input layer, the hidden layer, and the output layer respectively. These layers are connected. The whole learning process happens in the hidden layer, where neurons build a complex set of connections to find patterns [2]–[4].

III. Experimental Analysis with Machine Learning Simulation

A. The Database with Information about Foundations

In order to find links between the parameters and failure rate, a database had to be created. The database used to perform the simulation consisted of data obtained by private gas and oil company. Each of the foundations was designed and made for devices with different functions and purpose. There are many factors that can affect the failure rate of the machine foundations. The amount of data available and the complexity of the problem causes that not all data on foundations will be used. After consultation of the problem in the group of experts, nine variables were chosen, which are presented in Table Ⅰ.

TABLE I. Dataset Parameters Considered, as the Most Important.

Parameter	Codename	Type	Description
Measured concrete strength [MPa]	measured_concrete_strength	input	Data measured with a calibrated Schmidt hammer
The weight of the foundation [kN]	foundation_weight	input	Load from the weight of the foundation
Cross-section reinforcement [cm2]	rf_crosssection	input	The area of cross-section reinforcement steel
Grate [kN]	grate	input	Load from grate
The pump unit and rotor with shaft [kN]	machine_pump_rotor_with_shaft	input	Load from the pump unit and rotor with shaft
The engine unit and rotor with shaft [kN]	machine_engine_rotor_with_shaft	input	Load from the engine unit and rotor with shaft
Total load with fund. self-weight [kN]	total_with_self_weight	input	Total load
Load from motor short circuit [kNm]	load_moment_motor_shortcircuit	input	Load from the moment of motor short circuit
Foundation failure [1- yes, 0 -no]	foundations_failure_occurance	target	Checking if the failure has occurred or not

The parameters showed in Table Ⅰ are divided into two groups, targets, and inputs, which represents targeting results and input variables respectively. Ranges of input features are presented in Table Ⅱ.

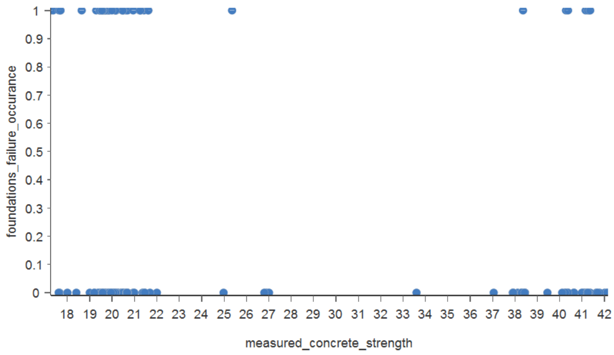
TABLE II. The Range of Database Input Features.

Input features	Minimum	Maximum	Average	Deviation
Measured concrete strength [MPa]	17,26	42,14	26,98	9,48
The weight of the foundation [kN]	24,91	3815,16	159,95	368,58
Cross-section reinforcement [cm2]	78	1120	176,08	112,57
Grate [kN]	0,48	14,22	1,72	1,37
The pump unit and rotor with shaft [kN]	0,44	16,48	4,51	3,67
The engine unit and rotor with shaft [kN]	0,64	192,21	10,36	19,87
Total load with fund. self-weight [kN]	85,63	4585,65	346,74	503,33

B. Machine Learning Simulation and Results

To carry out the analysis the data was divided into few subsets, the most important was the training dataset, required to build the model and the testing dataset, which is used to estimate the model performance. The total number of used records is 551. Training dataset contains 307 records (60,1%), the number of selection records is

102 (20,0%), and the testing dataset has 102 records (19.4%), none of the samples was excluded from the dataset. The scatter plots of two target variables versus the input variables are shown in Fig. 2.



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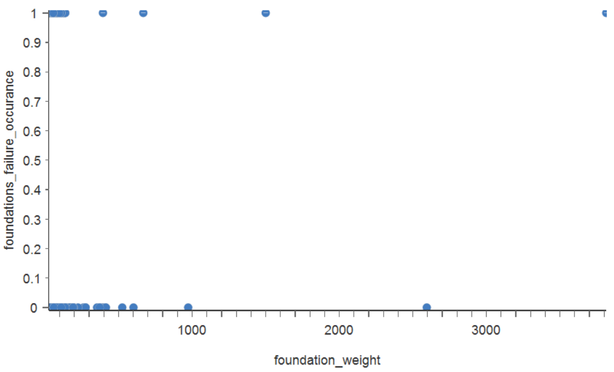

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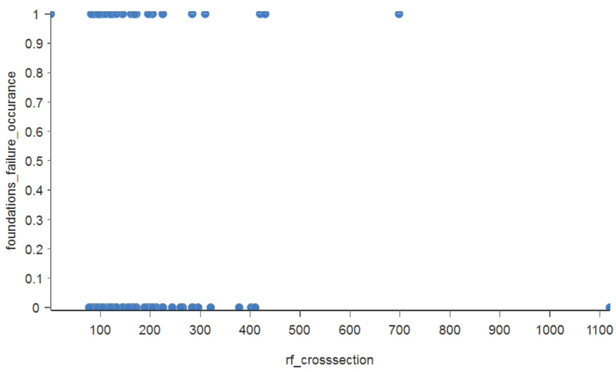

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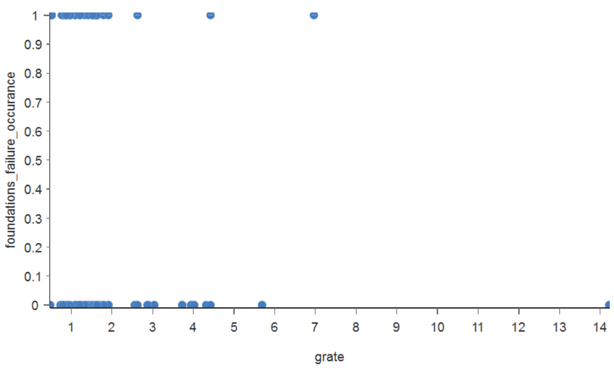

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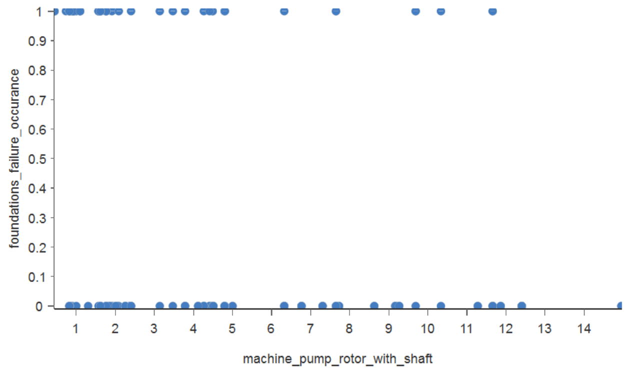

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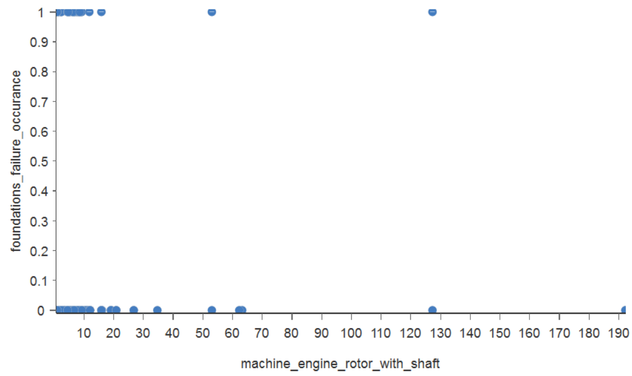

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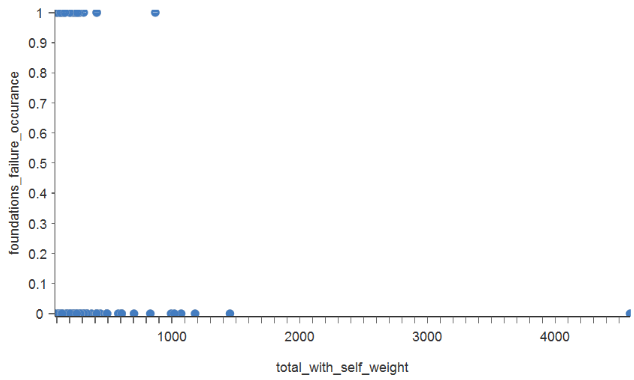

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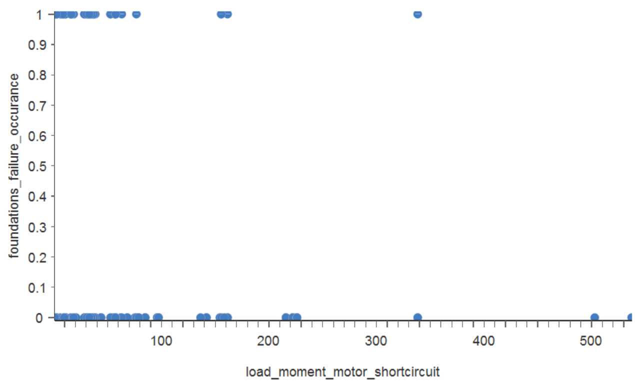

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Figure 2. The scatter plots – target versus input variables: a) Measured concrete strength [MPa], b) The weight of the foundation [kN], c) Cross-section reinforcement [cm2], d) Grate [kN], e) The pump unit and rotor with shaft [kN], f) The engine unit and rotor with shaft [kN], g) Total load with fund. self-weight [kN], h) Load from motor short circuit [kNm]. Target variable is the foundation failure occurrence [1- yes, 0 -no]

The initial architecture designed for the analysis is presented in Fig. 3. The model consists of eight input variables, which refers to eight principal components and generate one target outputs. The number of hidden neurons is four and represents the complexity of the model.

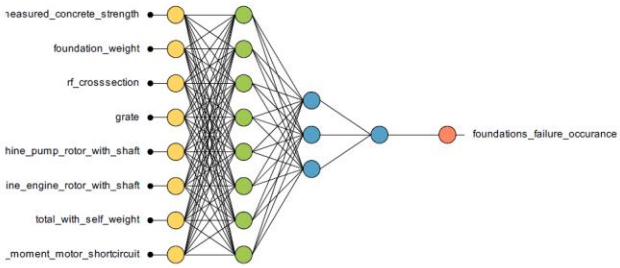


Figure 3. Initially used the architecture of the artificial neural network, the image shows network architecture, which apart of neural network (principal components are green, and perceptron neurons are blue) includes scaling (scaling neurons are yellow) and unscaling layer (unscaling neurons are red).

The authors used the BFGS method [5]–[10] to obtain a suitable training rate and Brent method [11]–[14] to calculate the step for the quasi-Newton training direction. The number of input neurons refers to some input variables, which can be described as influential towards failure occurrence. The target variables are associated with foundation failure occurrence. The analysis performed in this study requires to calculate the correlation matrix and linear correlation. Fig. 4 presents the importance of each input variable. It has to be noted that importance value greater than 1,0 imply that selection error has lower value without using that input variable. The value of 1,0 indicates the indifference of this variable to the result. The calculation reveals that the most important is the amount of reinforcement steel (gets a contribution of 252,3% to the outputs). The importance values were calculated by removing training input selectively and checking the output results.

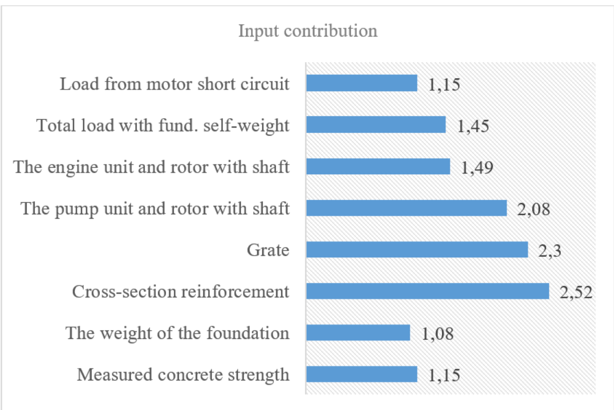


Figure 4. Input contribution.

Input selection was performed by growing inputs algorithm [15]–[18]. To perform a proper analysis, the authors must choose a model that will be suitable for a specific purpose and set of data. To handle that task the authors perform the order selection algorithm [19], [20] to find the optimal number of neurons. Output selection was performed by incremental order algorithm [21]–[23], the loss history for used subsets is presented in Fig. 5.

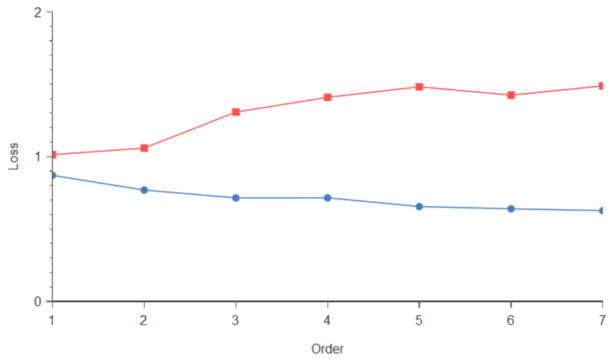


Figure 5. Incremental order algorithm performance – loss history (blue – training loss, red – selection loss).

A graphical representation of the resulted deep architecture is depicted next. It contains a scaling layer, a neural network, and an unscaling layer. The yellow circles represent scaling neurons, the blue circles perceptron neurons and the red circles unscaling neurons. The number of inputs is 4, and the number of outputs is 2. The complexity, represented by the numbers of hidden neurons, is 3. The most optimal neural network model finally adopted for performing the task is showed in Fig. 6.

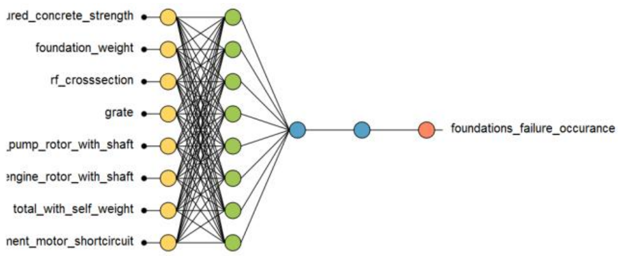
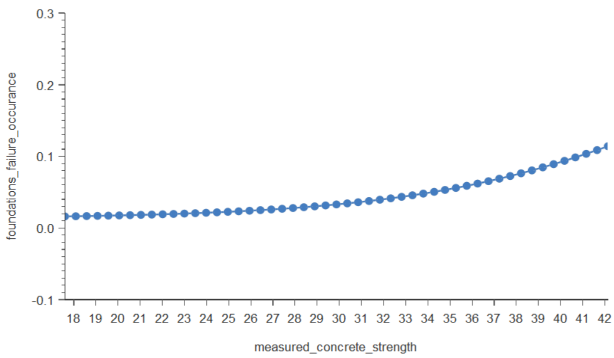


Figure 6. Finally used the architecture of the artificial neural network, the image shows network architecture, which apart of neural network (perceptron neurons are blue) includes scaling (scaling neurons are yellow) and unscaling layer (unscaling neurons are red).

The illustration of how the formula works is presented in the form of diagrams in Fig. 7. The diagrams show fluctuations in output vathe riables for a single input variable, while the others are fixed.



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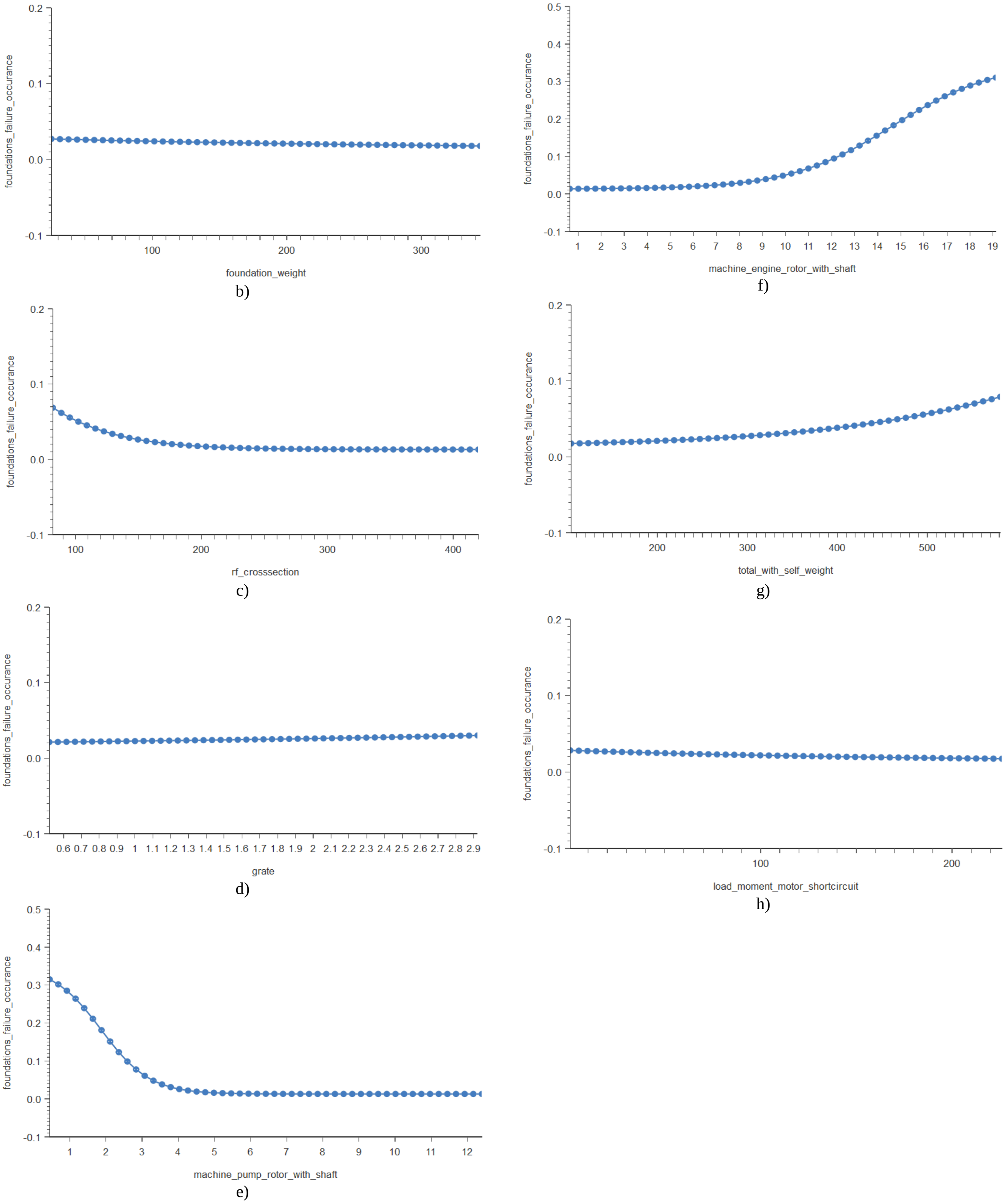

Figure 7. Output charts - the diagrams show fluctuations in output variables for a single input variable, while the others are fixed: a) Measured concrete strength [MPa], b) The weight of the foundation [kN], c) Cross-section reinforcement [cm2], d) Grate [kN], e) The pump unit and rotor with shaft [kN], f) The engine unit and rotor with shaft [kN], g) Total load with fund. self-weight [kN], h) Load from motor short circuit [kNm]. Target variable is the foundation failure occurrence.

IV. Summary and Conclusions

This paper presents the application of data mining and machine learning techniques in the examination of concrete machine foundations used in the gas and oil industry. The study aims to build the Artificial Neural Network model to process information about load effects impact for predicting foundations failure occurrence. For the needs of the study, we create a database of load effects combined with failure occurrence cases from private gas and oil company. The dataset consisted of 551 records and was divided to train adopted ANN model. Training dataset had 307 records (60,0%), there was 102 selection records (20,0%) and 102 testing records (20,0%), none of the samples was excluded from the dataset. The initially adopted ANN model has eight input variables, eight principal components, four hidden neurons, and one target output. The suitable training rate and the step for the quasi-Newton training direction were obtained by BFGS and Brent method respectively. The finally adopted ANN model has eight input variables, eight principal components, two hidden neurons, and one target output. The focal point of the analysis was to transform ANN code to the actual mathematical equation which can be used for practical purposes. Bearing in mind performed analysis, the following conclusions can be drawn. The amount of reinforcement has the most significant influence among all input variables. The lower “The pump unit and rotor with shaft” load value the greater chance of failures. The higher “The engine unit and rotor with shaft” load value the greater the chance of failures. No impact of "load from the moment of short-circuit of the motor" on the failures of the foundations. No impact of the "grid weight" load on the foundation failure rate. It was not possible right now to determine what effect has the amount of reinforcement and the measured concrete strength on the failure rate. It should be noted that the presented mathematical formula does not adequately reflect all the relationships between the variables. The authors would like to develop further with the presented method and, above all, build a model on a much broader set of data with more initial variables.

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