

Article

Validation Challenges in Data for Different Diesel Engine Performance Regimes Utilising HVO Fuel: A Study on the Application of Artificial Neural Networks for Emissions Prediction

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Abstract: Artificial neural networks (ANNs) provide supervised learning via input pattern assessment and effective resource management, thereby improving energy efficiency and predicting environmental fluctuations. The advanced technique of ANNs forecasts diesel engine emissions by collecting measurements during trial sessions. This study included experimental sessions to establish technical and ecological indicators for a diesel engine across several operational scenarios. VALLUM01, a novel tool, has been created with a user-friendly interface for data input/output, intended for the purposes of testing and prediction. There was a comprehensive collection of 12 input parameters and 10 output parameters that were identified as relevant and sufficient for the objectives of training, validation, and prediction. The proper value ranges for transforming into fuzzy sets for input/output to an ANN were found. Given that the ANN's training session comprises 1,000,000 epochs and 1000 perceptrons within a single-hidden layer, its effectiveness can be considered high. Many statistical distributions, including Pearson, Spearman, and Kendall, validate the prediction accuracy. The accuracy ranges from 96% on average, and in some instances, it may go up to 99%.

Keywords: artificial neural networks (ANNs); data validation problems; engine's emissions; diesel engine



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1. Introduction

Many technical and industrial problems [1] (predicting output parameters based on predicted or implied influencing factors) are addressed and solved by choosing the correct approximation function and evaluating the nature of the correlation [2]. However, this type of task quickly becomes too difficult when (a) there are many parameters that potentially influence the phenomenon, (b) the correlation is weak and insignificant, and (c) the previous approximations of a linear nature do not work or work with a large error. Many natural processes in complex nonlinear systems occur at very low speeds [3]. Over time, the process accelerates and approaches saturation [4]. In this case, it is possible to use artificial intelligence implementations that can solve atypical, incorrect, or large-scale sampling tasks.

An artificial neural network is a basic network consisting of an input layer, an output layer, and one or more intermediate neuron layers [5]. The main advantage of this network is that it evaluates input patterns after training [6]. For such a network, supervised learning

can be organized based on examples where input and output are linked by an event, or, in other words, a cause forms an effect (for example, experimental results of physical phenomena or function values obtained by an unknown formula, etc.). The essence of ANN training is that the desired output can be produced within a given error tolerance.

Artificial intelligence (AI) refers to the simulation of human intelligence in computer systems designed to solve problems in a human way [7]. AI systems are designed to analyze data, recognize patterns, make decisions, and improve over time through iterative learning processes or decision-making. Artificial intelligence can be used to monitor and manage resources [8], optimize energy consumption [9], and predict environmental changes to help address climate-related issues [10]. AI's main realization is ANN, which is based on the properties of biological neural networks. The structure and activity of the animal brain are modelled as a mathematical network of interconnected nodes (perceptron) divided into several layers: input, hidden, and output.

Several fundamental textbooks are interesting for understanding the newly developed paradigms of artificial neural networks. Zurada [11] defines the focus of the study of artificial neural systems. "Artificial neural systems are physical cellular systems that can acquire, store, and utilise experiential knowledge". Multilayer feedforward networks are presented and discussed in a user-friendly form. Rabunal et al. [12] described the processes of brain learning and the corresponding mathematical operations built up according to the analogy to brain activity. According to Rabunal, two main advantages of ANN are adaptive learning and fault tolerance. Adaptive learning is the ability to learn to perform tasks based on a training session that consists of selecting data specific to the task. Fault tolerance refers to the ability of a network to maintain its previous functions after a partial destruction of the network results in a corresponding performance degradation. Goodfellow et al. [13] presented the paradigm of deep learning, which allows a computer to construct complex concepts from simpler concepts. A significant example of a deep learning model is a multilayer perceptron (MLP). A mathematical function in the form of MPL associates some set of input values with output values. Torres-Sospedra [14] presented and discussed several design methods that are important for expanding the ANN. Lou [15] presented and discussed the abilities of neural networks, which belong to a subfield of machine learning.

Implementations of ANN for technical purposes (control and prediction of exhausts) were described in a series of contemporary publications.

Firstly, problems of data sampling must be solved within the framework of Big Data. Li et al. [16] presented a study that introduces a high-throughput fuel screening approach for early property-oriented fuel design in internal combustion engines. This process includes Tier 1 fuel physicochemical property screening and Tier 2 chemical kinetic screening. Ahmad et al. [17] claim that machine learning (ML) is one of the major driving forces behind the fourth industrial revolution. This study reviews the ML applications in the life cycle stages of biofuels, i.e., soil, feedstock, production, consumption, and emissions. The ML applications in the production stage include the estimation and optimization of quality, quantity, and process conditions. Usman et al. [18] presented the ANN-2HL-15 N model, among six trained models, which demonstrated exceptional efficiency in predicting operational effectiveness and discharge levels in small-scale single-cylinder SI engines. Its performance under optimal operating conditions improved emissions, CO, and HC emissions, as well as combustion. The combination of ANN and RSM promotes sustainable industrialization, conscientious consumption, and ethical production patterns, supporting SDGs 9 and 12.

Secondly, the implementation of ANN must be realized in a standalone manner as well as in close collaboration with other AI algorithms. Deng et al. [19] described the possibilities of ANN for engine application purposes (testing and diagnostics). Several models, such as the basic model for a fuel path control system, ANN to represent air flow rate, the Nox prediction ANN model, and the smoke prediction ANN model, are presented and estimated. Xing et al. [20] examine various aspects of control related to biodiesel production. Identifying unknown nonlinear relationships between the system input and output data is

not easy. Therefore, accurate and swift modelling instruments like M) or AI are necessary to design, handle, control, optimize, and monitor the system. Aliramezani et al. [21] presented ICE modelling for meeting emission regulations and minimizing fuel consumption. ML can tackle these challenges by addressing areas such as combustion knock detection, emission formation modelling, mode transition, combustion noise modelling, instability control, ICE optimization, and component fault diagnostics. Zhang et al. [22] studied a single model to simulate CO₂, CO, and Nox emissions from biodiesel combustion in compression ignition engines. The authors used three machine-learning tools to model the complex MIMO-type regression problem. The biodiesel source's physical features were found to be the best, and the MLS-SVR was the most reliable tool for estimating emissions. Khac et al. [23] present ANN-based models for estimating nitrogen oxide and carbon dioxide emissions from a maritime diesel engine's in-cylinder pressure. Using data from a four-cylinder engine, the models show MLP has higher accuracy than RBF, despite the engine's conventional nature and generalization to avoid overfitting. Žvirblis et al. [4] described the optimal prediction model for exhaust emission parameters. The optimal model predicted most engine emissions with high accuracy, but NO_x remained unpredictable. The interaction between injection timing and sound pressure remained statistically relevant. Engine emissions from the DF and HVO50 groups were not statistically different, with higher trends for PM, CO, HC, and NOX in the DF group. Injection timing had more influence on the distribution of emission parameters.

The problem of an algorithm suitable for ANN could be treated as a classical problem due to the impossibility of strong systematization of the calculation routine. Venkatesh et al. [24] studied the usage of 29 machine learning algorithms to estimate engine emissions in dual-fuel engines with hydrogen and diesel. The most effective algorithms included pace regression, radial basis function regressors, multilayer perceptron regressors, k-nearest neighbor, and alternating model trees. The J48 decision tree algorithm was used to establish the relationship. Leo et al. [25] used the random forest algorithm for evaluating the emissions of WCOB biodiesel with Al₂O₃ and FeCl₃ in a gasoline-premixed HCCI-DI engine. Results showed lower *BTE*, a 54.17% reduction in HC emissions, and decreased carbon dioxide emissions. Al₂O₃ nano-additives reduced smoke emissions by 30.4%, 24.8%, and 23.65%, respectively. Williams et al. [26] studied the random forest regression and neural network models to predict the rate-of-injection (ROI) profiles of a diesel injector. The neural network model performed better than the random forest model. Future work could include considering pressure, parameters, and larger input data, as well as focusing on ROI input in CFD simulations.

For prediction purposes, ANN is generally considered the most profitable model. Bekesiene et al. [27] examined complex stress factors in military service using an ANN model. Maximum accuracy was obtained using a multilayer perceptron neural network (MLPNN) with a 6-2-2 partition. The best ANN model was determined as the one that showed the smallest cross-entropy error. Jovanovic et al. [28] discussed how to implement neural networks in different programming languages. Here, the implementation of an arbitrary neural network in Java is examined. Godwin et al. [29] studied ANN and Ensemble LS Boosting to predict the combustion, performance, and emission parameters of an internal combustion engine using gasoline and ethanol blends. The ANN model demonstrated near-perfect precision in predicting key engine parameters, while the Ensemble LS Boosting model showed superior congruence with experimental engine parameters. The ensemble nature, resistance to overfitting, and optimized hyperparameters contributed to the Ensemble LS Boosting model's outstanding performance.

This work is based on experimental studies of the combustion characteristics, energy, and ecological indicators of a diesel engine carried out at Vilnius Tech.

The main aims of this work could be formulated as follows:

1. To construct an advanced tool with a user-friendly interface for data input and output facilities to provide simulations and predictions of exhausts in outcomes.

2. For an artificial neural network, construct the interfaces for input the layer and output layer (number of parameters, intervals) according to the general working principles of a diesel engine.
3. To establish the suitable parameters of ANN (number of hidden layers, amount of perceptron in the hidden layer), the number of training epochs must be chosen, which allows for the smallest deviation of the simulated value from the experimental value.
4. To provide the simulations and estimate simulated values within the framework of statistical distribution.

Diesel engines rely on several chemical reactions to produce energy: (i) the combustion reaction releases energy in the form of heat; (ii) the carbon and hydrogen atoms in the fuel molecules combine with oxygen from the air to form carbon dioxide (CO₂) and water (H₂O), along with the release of heat energy. In addition, the emissions may contain a wide variety of exhausts (NO, CO, HC, etc.). Different power regimes and unstable nonequilibrium states of combustion reactions are two factors that create uncertainty in the estimation and prediction of exhaust emissions. The correlations between the parameters of the diesel engine and the amount of exhaust products are weak and very weak. The presented paper's scientific novelty lies in its use of ANN to predict results based on experimental values obtained during measurement sessions.

2. Materials and Methods

2.1. Experimental Test Equipment and Materials

A compression-ignition, direct fuel injection turbocharged VW-Audi engine 1.9 TDI was used for experimental tests. Table 1 displays the engine's main technical characteristics.

Table 1. Main parameters of a 1.9 TDI compression ignition. Adapted according to [30].

Parameter	Units	Value
Displacement, V_H	dm ³	1.896
Number of cylinders, i	-	4/OHC
Number of engine strokes, τ	-	4
Compression ratio	-	19.5
Power	kW	66 (4000 rpm)
Torque	Nm	180 (2000–2500 rpm)
Bore	mm	79.5
Stroke	mm	95.5
Fuel injection	-	Direct injection (single)
Nozzle type and holder assembly	-	Hole-type, two spring
Nozzle opening pressure	bar	190

During the tests, the engine ran on a 100% renewable fuel—Hydrotreated Vegetable Oil. Pure Hydrotreated Vegetable Oil (HVO100) and pure fossil diesel (D100) have been tested in the laboratory [31] and meet the requirements of automotive fuel standards EN15940 and EN 590 [31]. Table 2 displays a comparison of the main properties of HVO100 and pure diesel D100. In the experimental research, pure biodiesel HVO100 and pure diesel D100 can be blended in different volume fraction percentages. This will change the properties of these fuel blends.

The engine control unit (ECU) controls the exhaust gas recirculation (EGR) system on the engine. During the test, the EGR system is disconnected from the ECU and controlled by a separate controller, which allows the EGR influence to be studied over a wide range. Similarly, the effect of the start of injection (SOI) on engine performance was investigated by disconnecting the control of the fuel injectors from the ECU and by using a separate controller to adjust the SOI. The actual SOI value is determined using a specialized VW-Audi diagnostic tool VCDS [33], which is connected to the on-board diagnostics (OBD) connector on the ECU. SOI units are crank angle degree before top dead centre (CAD

bTDC), with a measurement accuracy of 0.5 CAD. A scheme of engine test equipment is shown in Figure 1.

Table 2. Main properties of the fuels tested. Adapted according to [32].

Properties	Units	HVO100	EN 15940	D100	EN 590
Density at 15 °C	g/mL	0.782	0.765–0.800	0.838	0.820–0.845
Kinematic viscosity at 40 °C	cSt	2.876	2.000–4.500	2.9401	2.000–4.500
Cold filter plugging point	°C	−44	≤+5... ≤−44 *	−22	≤+5... ≤−44 *
Pour point	°C	<−50	≤−10 *... ≤−34 *	−39	≤−10 *... ≤−34 *
Flash point	°C	65.0	> 55.0	74.8	>55.0
Water content	% V/V	0.0021	≤0.020	0.0028	≤0.020
Lubricity	µm	344	≤460	406	≤460
Cetane number	-	74.3	≥70	~53	≥51.0
Elemental composition (H)	%	15.62	-	13.31	-
Elemental composition (C)	%	84.38	-	86.69	-
C/H ratio		5.40	-	6.51	-
Stoichiometric air to fuel ratio (I_0)	kg air/1 kg fuel	15.10	-	14.50	-
Lower heating value (LHV)	MJ/kg	43.63	≈44	42.83	≈43

* Severe winter and arctic grades.

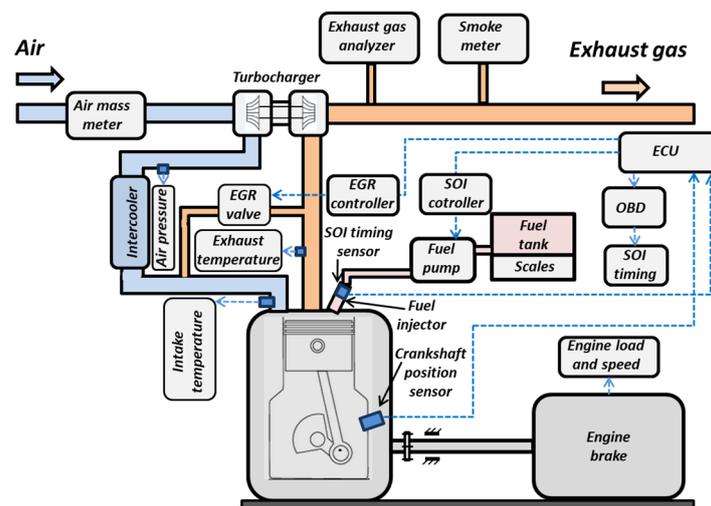


Figure 1. Scheme of engine test equipment.

The engine brake stand (KI-5543) is used to load the engine with the selected brake torque (M_B). Brake torque loads of 30 Nm, 60 Nm, 90 Nm, and 120 Nm are used. The accuracy of the M_B measurement is ± 1.23 Nm. The engine speed was set to $n = 2000$ rpm and $n = 2500$ rpm. In order to ensure that the engine operates in a wide range of possible modes, the SOI and EGR strategies were varied during the testing at different speeds and loads. The results section contains more details on the experimental regimes (seven stages).

Fuel consumption was measured using an AMX 212F gravity scale, which measures the fuel flow of 0.01...50 kg/h with an accuracy of $\pm 0.1\%$. Air consumption was measured with a BOSCH HFM 5 air mass meter, which measures an air flow rate of 8...370 kg/h with an accuracy of $\pm 2\%$. An AVL DiCom 4000 gas analyser was used to measure pollutants. CO₂ measuring range 0...20%, accuracy $\pm 0.1\%$; CO measuring range 0...10%, accuracy $\pm 0.01\%$; HC measuring range 0...20000 ppm, accuracy ± 1 ppm; NO_x measuring range 0...5000 ppm, accuracy ± 1 ppm; O₂ measuring range 0...25%, accuracy $\pm 0.01\%$; and smokiness (opacity) measuring range 0...99.99%, accuracy $\pm 0.01\%$. The engine characteristics were calculated according to the routine equations presented in [34]. Engine braking (loading) power:

$$P_B = \frac{M_B \cdot n}{9549}, [\text{kW}]. \quad (1)$$

Engine load is converted to a specific value—brake means effective pressure:

$$BMEP = \frac{M_B \cdot 30 \cdot \tau}{V_H \cdot 9549}, [\text{MPa}]. \quad (2)$$

The brake torques to be provided are equivalent to *BMEPs* of 0.2 MPa, 0.4 MPa, 0.6 MPa, and 0.8 MPa. Fuel consumption was measured using an electronic scale (SK-5000) and a stopwatch, and the hourly fuel consumption B_f was determined with an accuracy of 0.5%. Brake specific fuel consumption:

$$BSFC = \frac{B_f \cdot 1000}{P_B}, \left[\frac{\text{g}}{\text{kWh}} \right]. \quad (3)$$

Brake thermal efficiency (*BTE*) calculated by considering the power output of the engine and the energy supplied by the fuel:

$$BTE = \frac{P_B \cdot 3.6}{B_f \cdot LHV}, \quad (4)$$

The air inlet to the engine B_{air} is measured with a BOSCH HFM 5 air mass meter (measuring range 8–370 kg/h, accuracy $\pm 2\%$). Using information on fuel and air mass consumption and the stoichiometric air to fuel ratio (l_0), the excess air ratio is calculated:

$$\lambda = \frac{B_{air}}{B_f \cdot l_0}. \quad (5)$$

The mass of exhaust gases returned to the cylinder is determined by considering the mass of air intake into the cylinders when EGR is off (B_{air}) and the mass of air when EGR is on (B_{air_EGR}) and the engine is running at the same load and speed:

$$B_{EGR} = B_{air} - B_{air_EGR}, \left[\frac{\text{kg}}{\text{h}} \right]. \quad (6)$$

EGR ratio:

$$EGR = \frac{B_{EGR}}{B_{air_EGR} + B_{EGR}}, \quad (7)$$

The exhaust gas analyser AVL DICOM 4000 is used to measure the exhaust gas composition—the volumetric concentration of various components. Carbon monoxide (CO) measurement range 0–10% (vol.), accuracy 0.01%; carbon dioxide (CO₂) measurement range 0–20% (vol.), accuracy 0.1%; hydrocarbons (HC) measuring range 0–20,000 ppm (vol.), accuracy 1 ppm; nitrogen oxides (NO_x) measuring range 0–5000 ppm (vol.), accuracy 1 ppm; smoke opacity (SO) measurement range 0–99.99%, accuracy 0.01%. The mass flows of individual exhausts (B_{CO} , B_{CO_2} , B_{HC} , B_{NO_x}) are calculated by taking into account the engine's air and fuel consumption (B_{air} , B_f), the concentration of the exhausts, and their specific properties. Specific emissions are the mass of exhaust per unit of engine power. For example, specific emissions of CO include the following:

$$SCO = \frac{B_{CO} \cdot 1000}{P_B}, \left[\frac{\text{g}}{\text{kWh}} \right], \quad (8)$$

For other exhausts (SCO_2 , SHC , and SNO_x), specific emissions are calculated in the same way.

2.2. Data Collection

Input data consists of fuel properties (cetane number, volume fraction of HVO100, C/H ratio, l_0 , λ , LHV , density) and engine control parameters (engine speed, *BMEP*, *SOI*, *EGR*). The output data consists of the engine's energy performance (*BSFC*, *BTE*), exhaust gas

concentration (CO_2 , O_2 , NO_x), and specific emissions (CO , CO_2 , HC , NO_x , and smokiness). The input data distribution ranges have been chosen because the engine can run on a wide range of fuel compositions when varying the ratio of D100 to HVO100 in the fuel. Fuel blends may also contain other additives that change the fuel properties. The engine can operate over a wide range of loads and speeds, with different EGR and SOI settings in different modes. The interval limits for the output parameters are based on the experience of various experimental studies in different modes of engine operation. Tables 3 and 4 represent the experimental parameters of the diesel engine used for ANN as input and output, respectively. Output parameters were divided into three clusters (according to increased order index). The first cluster contains volumetric O_2 concentration (R08), SNO_x (R04), and volumetric concentration of NO_x (R09). The second cluster contains smoke (R00), brake specific fuel consumption (*BSFC*) (R01), and brake thermal efficiency (*BTE*) (R02). The third cluster contains *SHC* (R05), *SCO* (R03), volumetric CO_2 concentration (R07), and SCO_2 (R06).

Table 3. Experimental parameters of diesel engine used for an ANN as the input parameters.

Index	Abbr.	Parameter	Units	Interval	
				X_{MIN}	X_{MAX}
0	P10	The excess air ratio (λ)	-	1.0	10.0
1	P03	Brake mean effective pressure (<i>BMEP</i>)	MPa	0.0	1.2
2	P02	<i>EGR</i> ratio	-	0.0	0.5
3	P11	Start of injection (SOI)	CA bTDC	-3.0	18.0
4	P09	Cetane number	-	5.0	85.0
5	P01	Engine speed (n)	rpm	800.0	4000.0
6	P04	Volume fraction of HVO100	%	0.0	100.0
7	P05	Volume fraction of D100	%	0.0	100.0
8	P12	C/H ratio	-	5.0	7.0
9	P06	Stoichiometric air to fuel ratio (I_0)	1 kg of air/1 kg of fuel	10.0	20.0
10	P08	Lower heating value (<i>LHV</i>)	$\text{MJ}\cdot\text{kg}^{-1}$	18.0	60.0
11	P07	Density	$\text{kg}\cdot\text{m}^{-3}$	600.0	900.0

Table 4. Experimental parameters of diesel engine used for ANN as the output parameters.

Index	Abbr.	Parameter	Units	Interval	
				Y_{MIN}	Y_{MAX}
0	R03	<i>SCO</i>	$\text{g}\cdot\text{kWh}^{-1}$	0.5	10.0
1	R07	Volumetric CO_2 concentration	%	0.1	15.0
2	R06	SCO_2	$\text{g}\cdot\text{kWh}^{-1}$	100.0	2000.0
3	R00	Smokiness	m^{-1}	0.001	100.0
4	R01	Brake specific fuel consumption (<i>BSFC</i>)	$\text{g}\cdot\text{kWh}^{-1}$	150.0	3000.0
5	R02	Brake thermal efficiency (<i>BTE</i>)	-	0.01	0.5
6	R05	<i>SHC</i>	$\text{g}\cdot\text{kWh}^{-1}$	0.01	2.0
7	R08	Volumetric O_2 concentration	%	0.5	20.0
8	R04	SNO_x	$\text{g}\cdot\text{kWh}^{-1}$	0.1	20.0
9	R09	Volumetric NO_x concentration	ppm	10.0	10,000.0

2.3. Principal Scheme of Tool VALLUM01

The advanced tool VALLUM01 [35] was constructed according to schemes presented in Figures 2 and 3. Two different modules (a) for data conversion (from any real interval to fuzzy logic interval (0;1), forward and backward, see Figure 2) and (b) implementation of an ANN (see Figure 3) represent the main engines of the current project VALLUM01. All inputs are aggregated into the input layer, $L = 12$, all inputs are aggregated into the output layer $N = 10$. This ANN represents the implementation of one internal layer (called hidden), consisting of a requested number of perceptron $M = (500;1000)$. Due to adjusting

possibilities, bias was included in the hidden layer. The programmed package VALLUM01, which contains a graphical, user-friendly interface for input, output, and control, was created using the JAVA Eclipse framework. For ANNs, two typical classes from [36] were used: matrix and neural network. As an S-shaped function, a sigmoidal function was used:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (9)$$

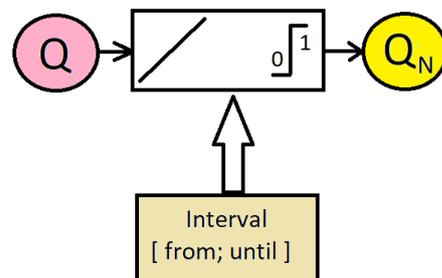


Figure 2. Advanced tool VALLUM01: scheme of data input/output.

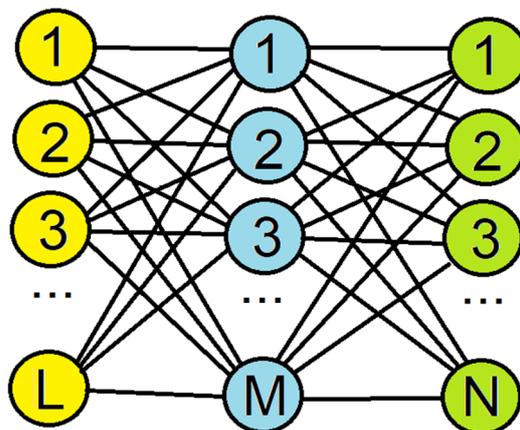


Figure 3. Scheme of an artificial neural network (ANN): input layer, number of units $L = 12$, single-hidden layer, number of perceptron $M = (500;1000)$, output layer, number of units $N = 10$.

2.4. Organization of Data Input/Output

Real input data of the P01-P12 type (aggregated into the input layer, number of units $L = 12$) and real output data of the R00-R09 type (aggregated into the output layer, number of units $N = 10$), which express strong defined measurable physical quantities (see Tables 3 and 4), were selected and approved for development. For an artificial neural network (ANN), input and output values must be presented in normalised form, which expresses the behaviour of fuzzy logic in the interval (0;1). Due to that, for all real values, the interval of distribution (X_{MIN} ; X_{MAX}) was initially established (see Tables 3 and 4). The module of data conversion recalculates the experimental input values X_i ($i = 0; L$) and output values Y_j ($j = 0; N$) to corresponding fuzzy logic values XX_i and YY_j in a forward or backward direction according to the formulas, respectively:

$$XX_i = \frac{X_i - X_{MIN}}{X_{MAX} - X_{MIN}} \quad (10)$$

$$X_i = X_{MIN} + XX_i(X_{MAX} - X_{MIN}) \quad (11)$$

2.5. Test Campaign

Figure 4 represents the distribution of experimental events (the current working state of the diesel engine) related to the different technical regimes (enumerated as 1..40).

Experimental testing was carried out with the engine running at different speeds with varying loads, EGR, and SOI:

- In the I stage (regimes 1–4, events, 1–30), the engine speed was set at 2000 rpm and the load was set at 30 Nm, 60 Nm, 90 Nm, and 120 Nm; the EGR was switched off, and the SOI (2–5 CAD bTDC) was controlled by the ECU.
- In the II stage (regimes 5–8, events 31–52), the engine speed was set at 2500 rpm and the load was set at 30 Nm, 60 Nm, 90 Nm, and 120 Nm; the EGR was switched off, and the SOI (5–12 CAD bTDC) was controlled by the ECU.
- In the III stage (regimes 11–14, events 53–76), the engine speed (2000 rpm) and load (60 Nm) were fixed, the EGR ratio was changed (0.05; 0.10; 0.15 and 0.20) using an EGR controller, and the SOI (3–4 CAD bTDC) was controlled by the ECU.
- In the IV stage (regimes 15–23, 77–112), the engine speed (2000 rpm) and load (60 Nm) were fixed, EGR = 0.15 was set by the EGR controller, and fuel injection was changed by the SOI controller in the range of $-3-15$ CAD bTDC.
- In the V stage (regimes 24–27, 113–140), the engine speed was set at 2500 rpm and the load was set at 30 Nm, 60 Nm, 90 Nm, and 120 Nm; the EGR ratio (0.35–0.05) and the SOI (5–10 CAD bTDC) were controlled by the ECU.
- In the VI stage (regimes 28–31, 141–159), the engine speed was set at 2500 rpm and the load was set at 30 Nm, 60 Nm, 90 Nm, and 120 Nm; the EGR ratio (0.45–0.20) and the SOI (2–5 CAD bTDC) were controlled by the ECU.
- In the VII stage (regimes 32–40, 160–195), the engine speed (2000 rpm) and load (60 Nm) were fixed, the controller set to EGR = 0.2, and the SOI controller varied the start of injection in the range of $-3-15$ CAD bTDC.

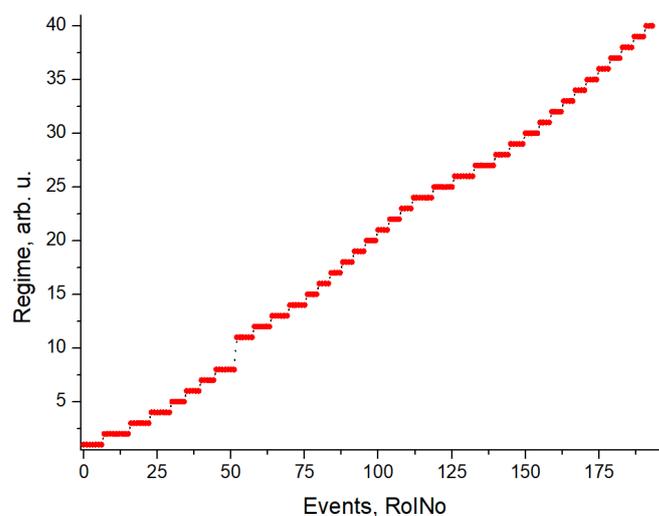


Figure 4. Experimental events (0...196) related to the different technical regimes (1...40) of diesel engines.

In these experimental studies, the engine was controlled both by the ECU's default algorithm, by further modification of the control parameters, and by extending the field of operations.

3. Results

Simulations (training of ANN and output validation as a special case of prediction) were provided using a desktop computer, 11th Gen Intel(R) Core (TM) i5-11600K, 3.90 GHz, 32.0 GB RAM, and OS Windows 10 Pro. Programming package VALLUM01 (implementation of ANN in the regime of backpropagation, one hidden layer) was used for training and validation. The learning rate for training was established at 0.01 (without changes). Table 5 represents several simulation regimes for the usage and validation of ANN.

First, two training data sets (abc1.csv and bcd1.csv) consisting of P01–P12 and R00–R09 types were prepared. The set abc1.csv (size 194 events) represents pure experimental data without any filtering or mathematical development. Set abc1.csv consists of 40 subsets corresponding to the different technical regimes of diesel engines as presented in Figure 4. Set bcd1.csv (size 38 events) represents averaged data only (one averaged value per regime).

Second, six simulations (using different hidden layer, $M = (500; 1000)$) for the validation of the data in the abc1.csv file were provided. Several different training routines T1–T6 were used by selecting the training data set (abc1.csv, real values of 194 events or, bcd1.csv, averaged values of 38 events, respectively), as well as by changing the number of training epochs (500,000; 1,000,000). Training was provided using the learning rate value of 0.01. Table 6 represents the distribution of the total network error (TNE), or *error* on the number of training epochs for different training regimes T1–T6: predefined by the number of training events and the number of perceptrons in hidden layers.

$$TNE^2 = \frac{1}{N} \sum_{i=1}^N (X_i^{current} - Target_i)^2 \tag{12}$$

Table 5. The procedure of training and validation of ANNs. Input layer $L = 12$, output layer $N = 10$, amount of perceptron in the hidden layer M , learning rate 0.01.

Project	One Hidden Layer			Training			Validation	
Name	M	Routine	File	Events	Epochs	TNE^2	File	Events
aaaa	500	T1	abc1.csv	194	500,000	Tables 7–12	abc1.csv	194
bbbb	500	T2	bcd1.csv	38	500,000	Tables 7–12	abc1.csv	194
cccc	1000	T3	abc1.csv	194	500,000	Tables 7–12	abc1.csv	194
dddd	1000	T4	bcd1.csv	38	500,000	Tables 7–12	abc1.csv	194
eeee	1000	T5	abc1.csv	194	1,000,000	Tables 7–12	abc1.csv	194
ffff	1000	T6	bcd1.csv	38	1,000,000	Tables 7–12	abc1.csv	194

Table 6. Distribution of the TNE^2 on the number of training epochs for different training regimes T1–T6: predefined by number of training events and number of hidden layers.

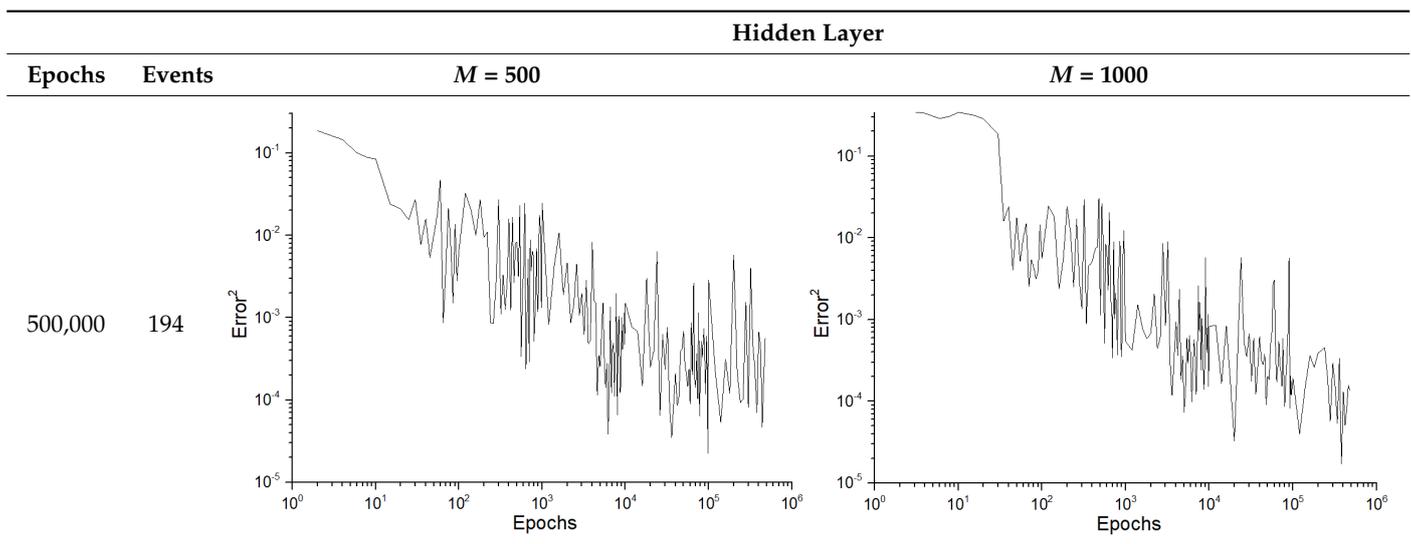
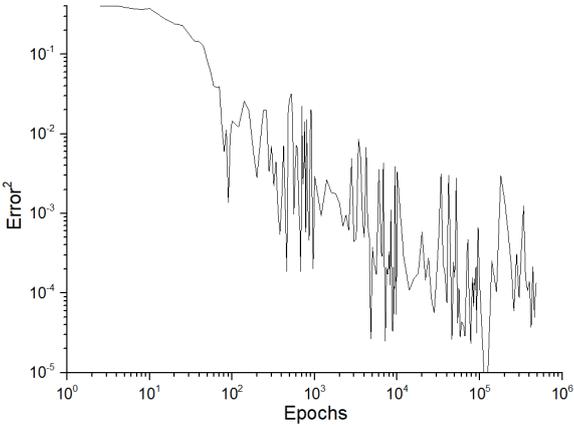
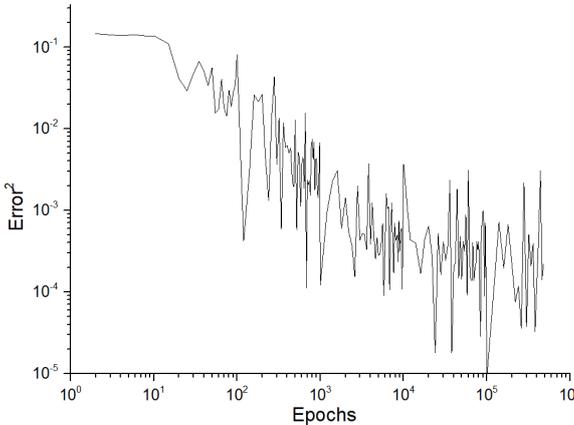
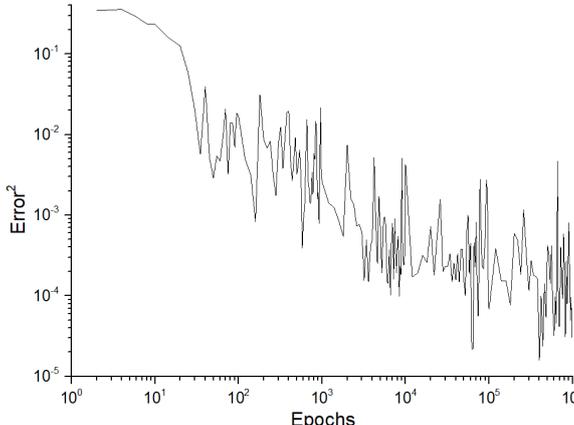
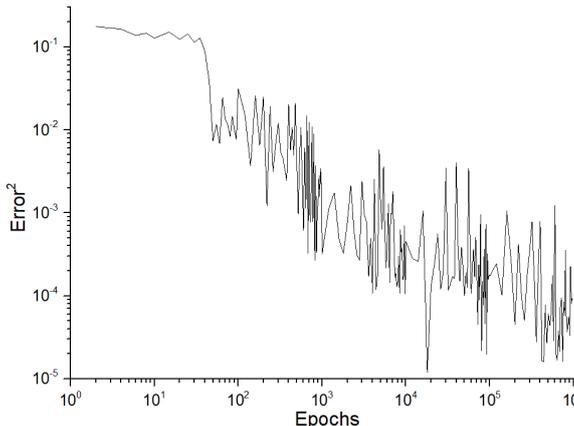


Table 6. Cont.

		Hidden Layer	
Epochs	Events	$M = 500$	$M = 1000$
500,000	38		
1,000,000	194	x	
1,000,000	38	x	

Tables 7–12 represent the results of validation after training the ANN using different training regimes (T1–T6). Results are presented in the form of a triplet (R as the real experimental value, R* as predicted using the T1, T3, and T5 routine, and R** as predicted using the T2, T4, and T6 routine). Tables 7, 9 and 11 represent distributions of predicted values R03, R07, R06, R00, and R01 and corresponding Pearson diagrams, and Tables 8, 10 and 12 represent distributions of predicted values R02, R05, R08, R04, and R09 and corresponding Pearson diagrams. The smallest deviations between experimental and simulated values were obtained using training routines the T5 and T6 (see Table 5).

Table 7. Results of validation after training of ANNs (one hidden layer, $M = 500$). Distributions of predicted values R03, R07, R06, R00, and R01 and corresponding Pearson diagrams. Two different training routines T1 and T2 were used (see Table 5). Number of training epochs: 500,000. Distributions of values: R as real experimental value, R* as predicted using T1 routine, and R** as predicted using T2 routine). Number of events for validation 194.

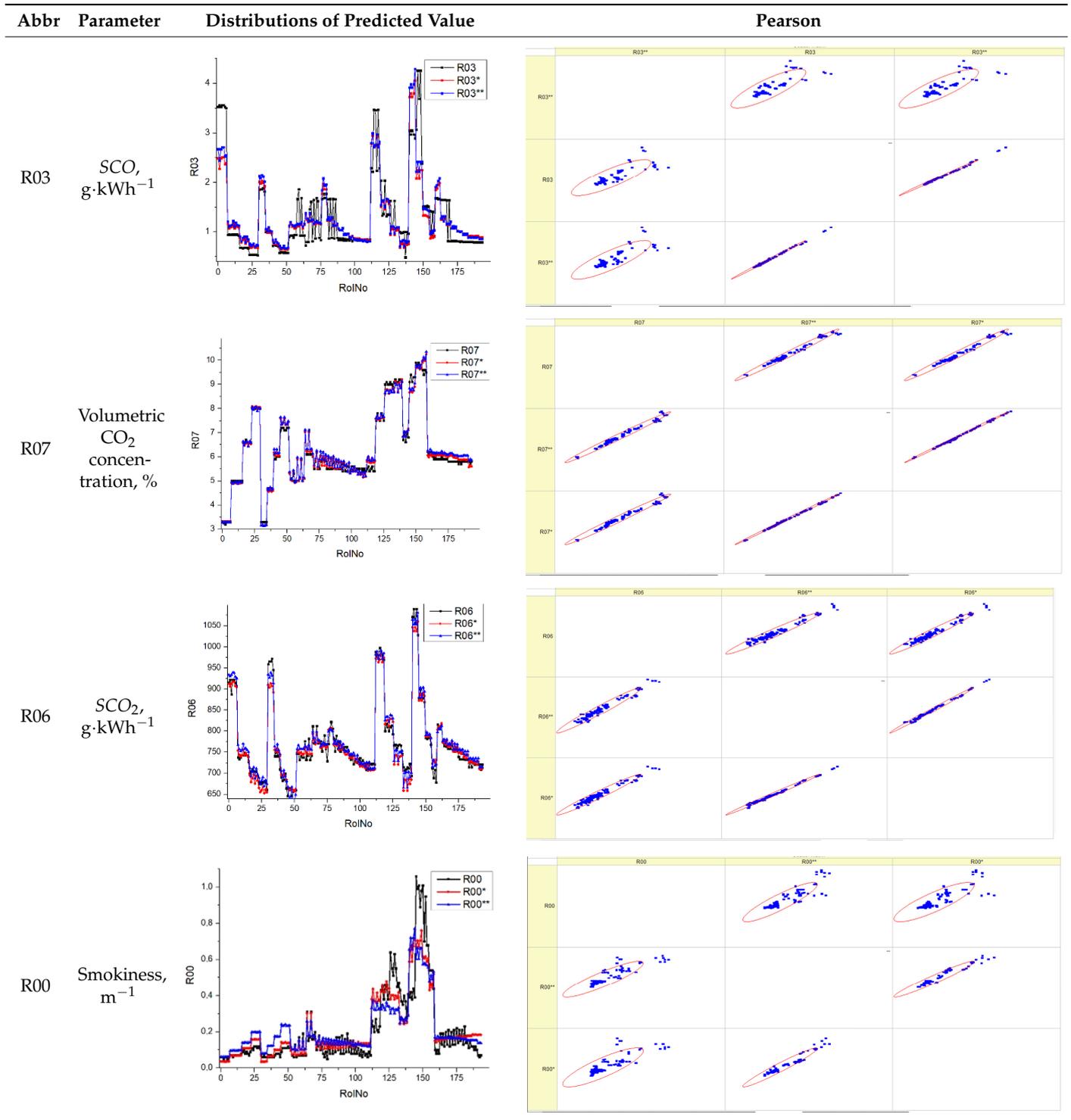


Table 7. Cont.

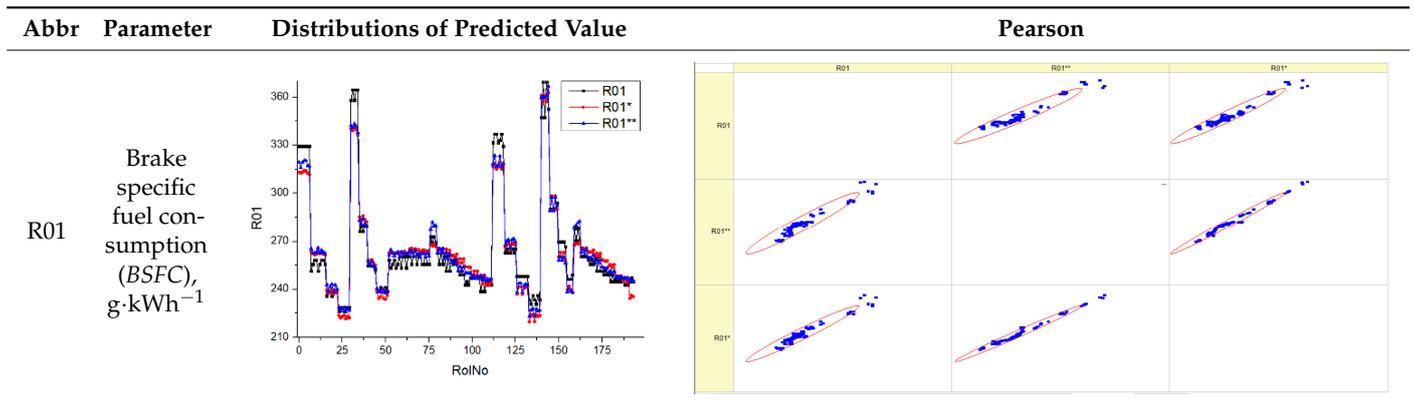


Table 8. Results of validation after training of ANN (one hidden layer, $M = 500$). Distributions of predicted values R02, R05, R08, R04, and R09 and corresponding Pearson diagrams. Two different training routines T1 and T2 were used (see Table 5). Number of training epochs: 500,000. Distributions of values: R as real experimental value, R^* as predicted using the T1 routine, and R^{**} as predicted using the T2 routine. Number of events for validation 194.

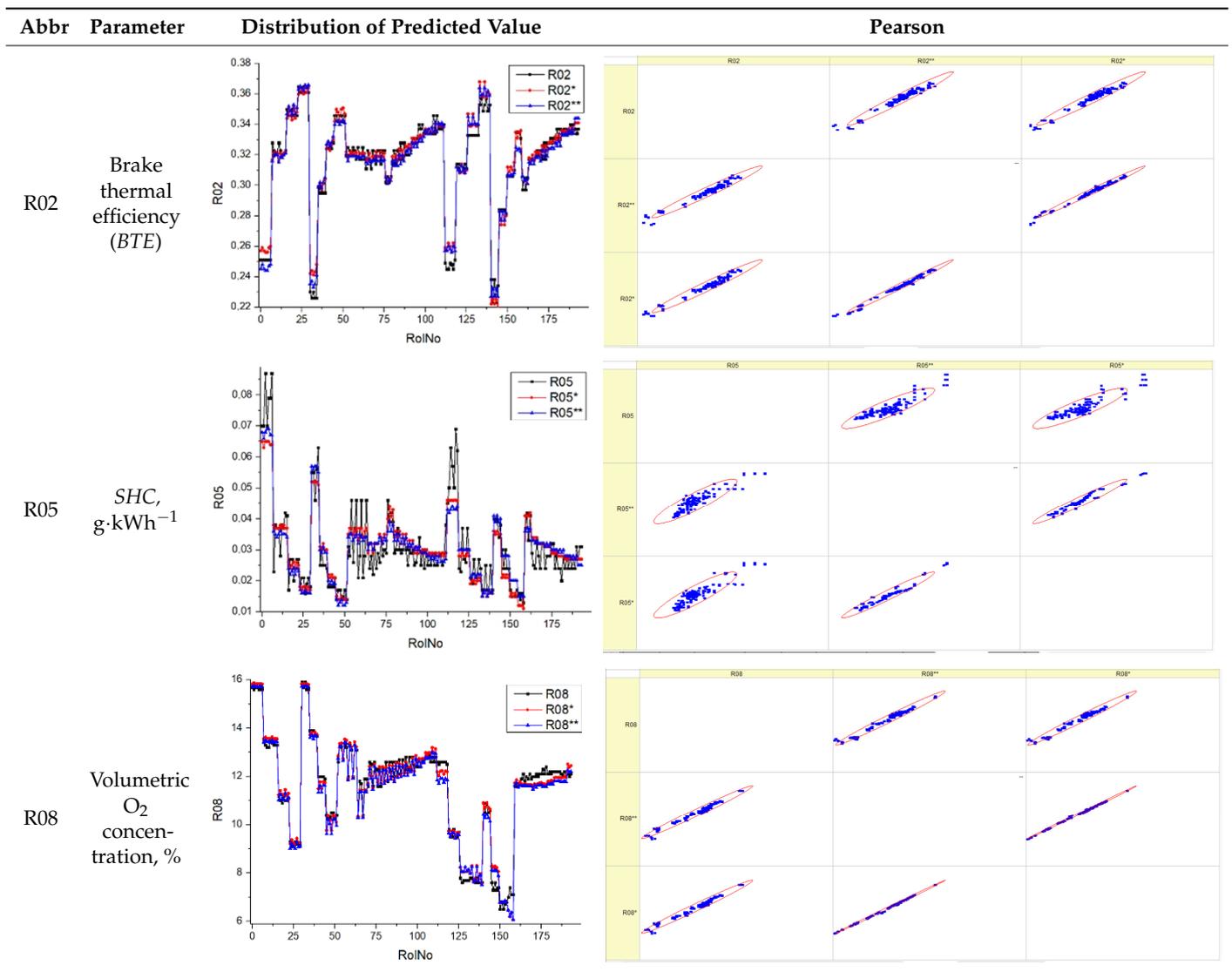


Table 8. Cont.

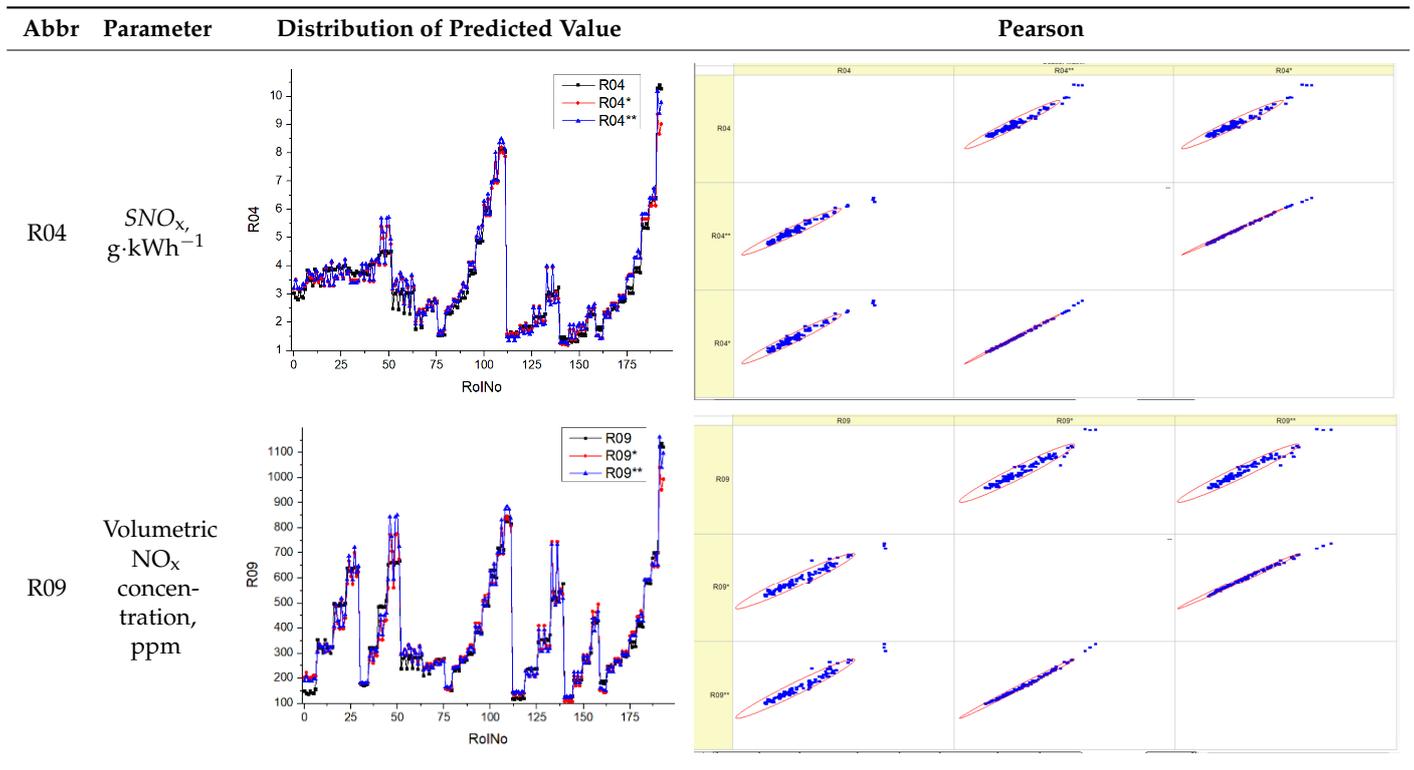


Table 9. Results of validation after training of ANNs (one hidden layer, $M = 1000$). Distributions of predicted values R03, R07, R06, R00, and R01 and corresponding Pearson diagrams. Two different training routines T3 and T4 were used (see Table 5). Number of training epochs 500,000. Distributions of values: R as real experimental value, R^* as predicted using the T3 routine, and R^{**} as predicted using T4 routine. Number of events for validation 194.

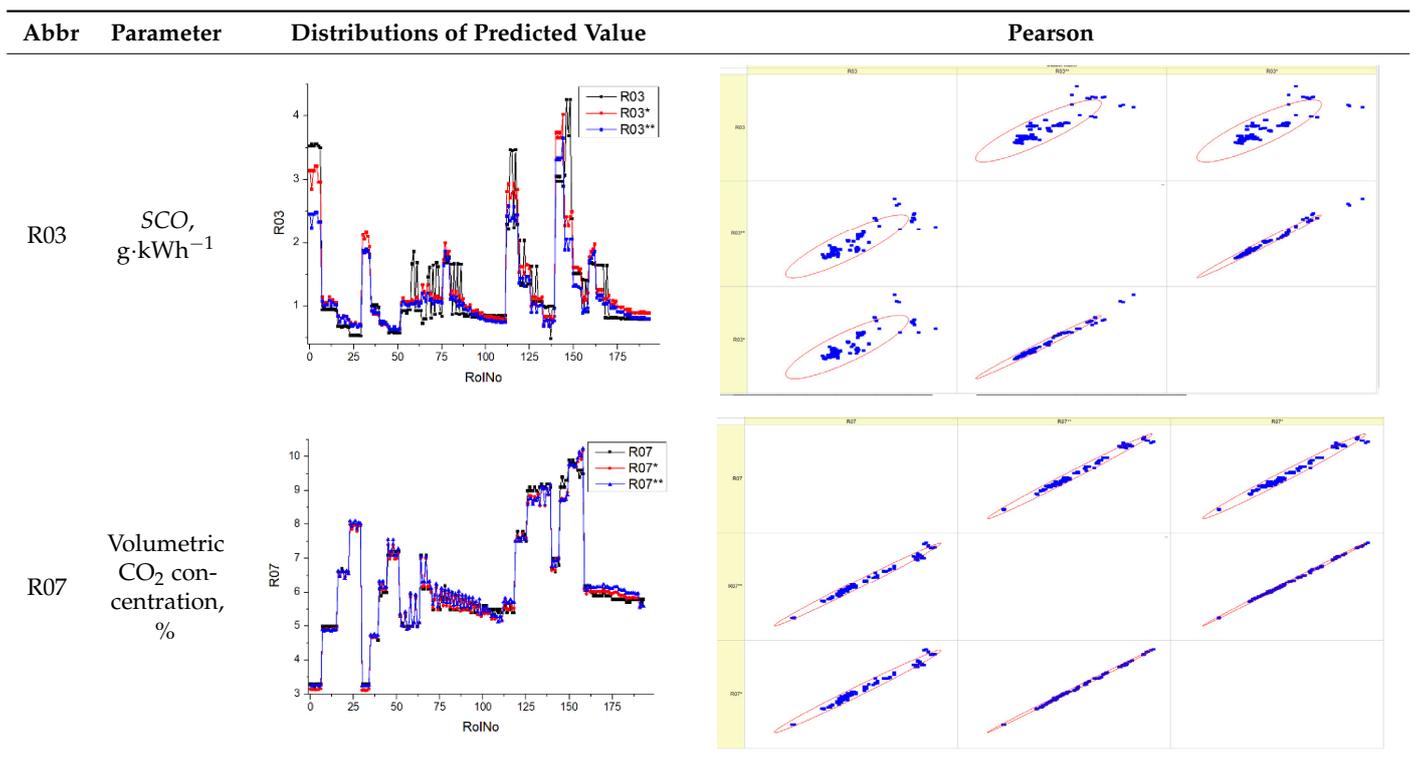


Table 9. Cont.

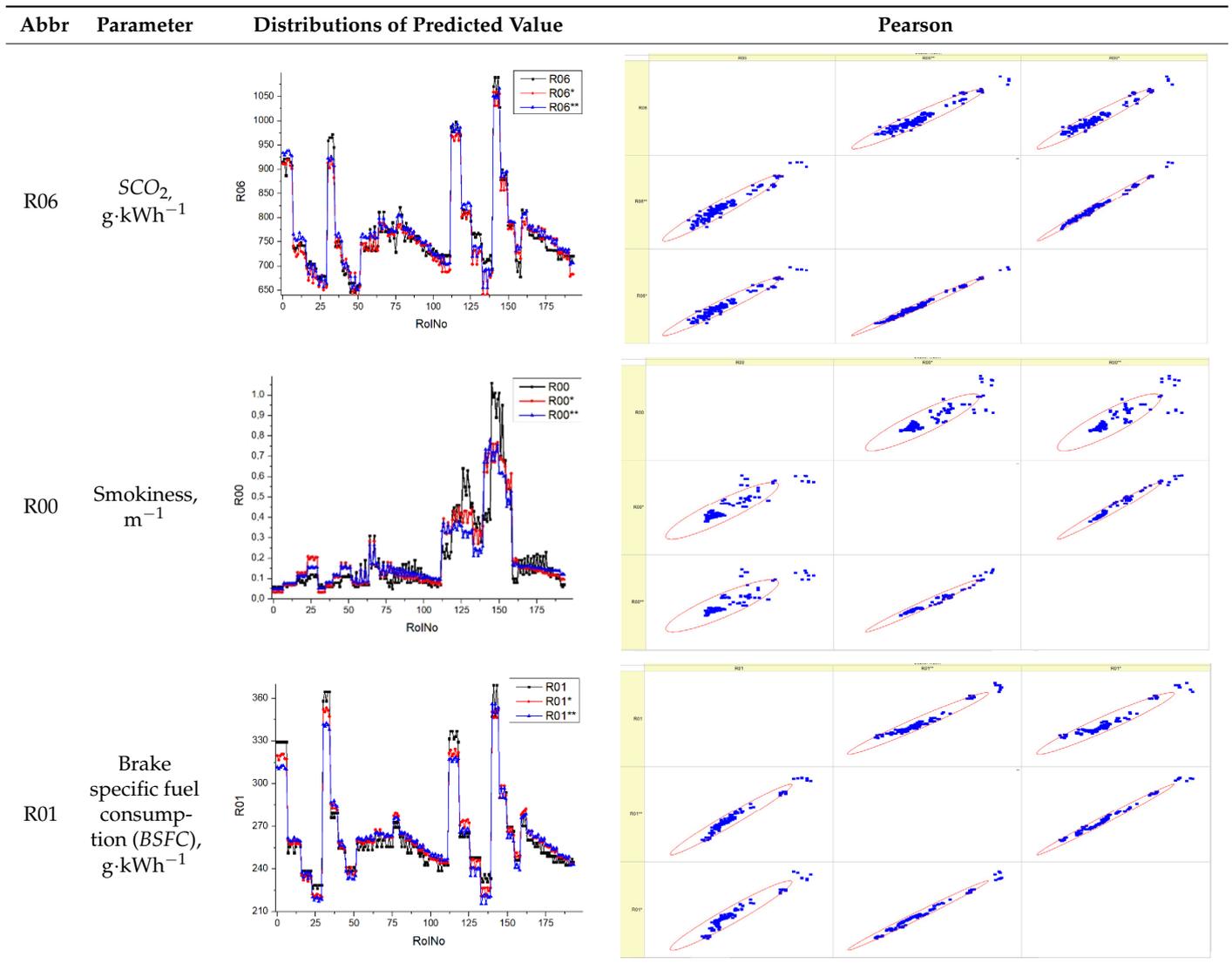


Table 10. Results of validation after training of ANNs (one hidden layer, $M = 1000$). Distributions of predicted values R02, R05, R08, R04, and R09 and corresponding Pearson diagrams. Two different training routines T3 and T4 were used (see Table 5). Number of training epochs: 500,000. Distributions of values: R as real experimental value, R^* as predicted using the T3 routine, and R^{**} as predicted using the T4 routine. Number of events for validation 194.

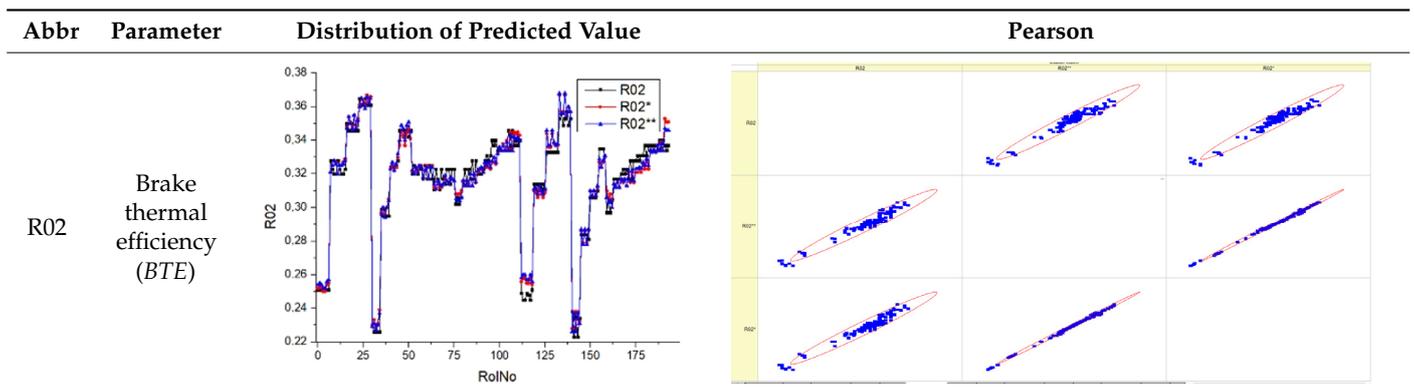


Table 10. Cont.

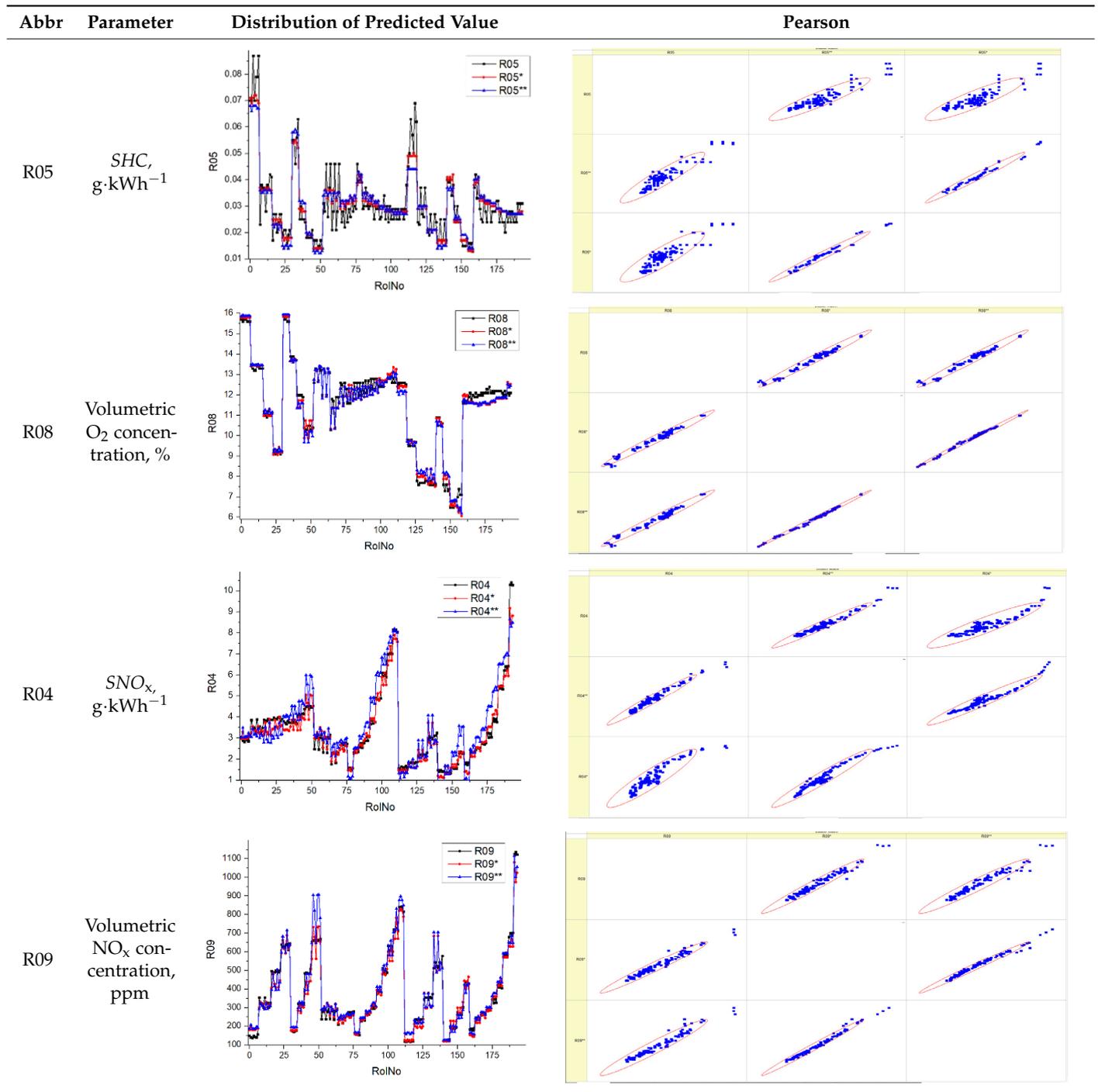


Table 11. Results of validation after training of ANNs (one hidden layer, $M = 1000$). Distributions of predicted values R03, R07, R06, R00, and R01 and corresponding Pearson diagrams. Two different training routines T5 and T6 were used (see Table 5). Number of training epochs: 1,000,000. Distributions of values: R as real experimental value, R^* as predicted using the T5 routine, and R^{**} as predicted using the T6 routine. Number of events for validation 194.

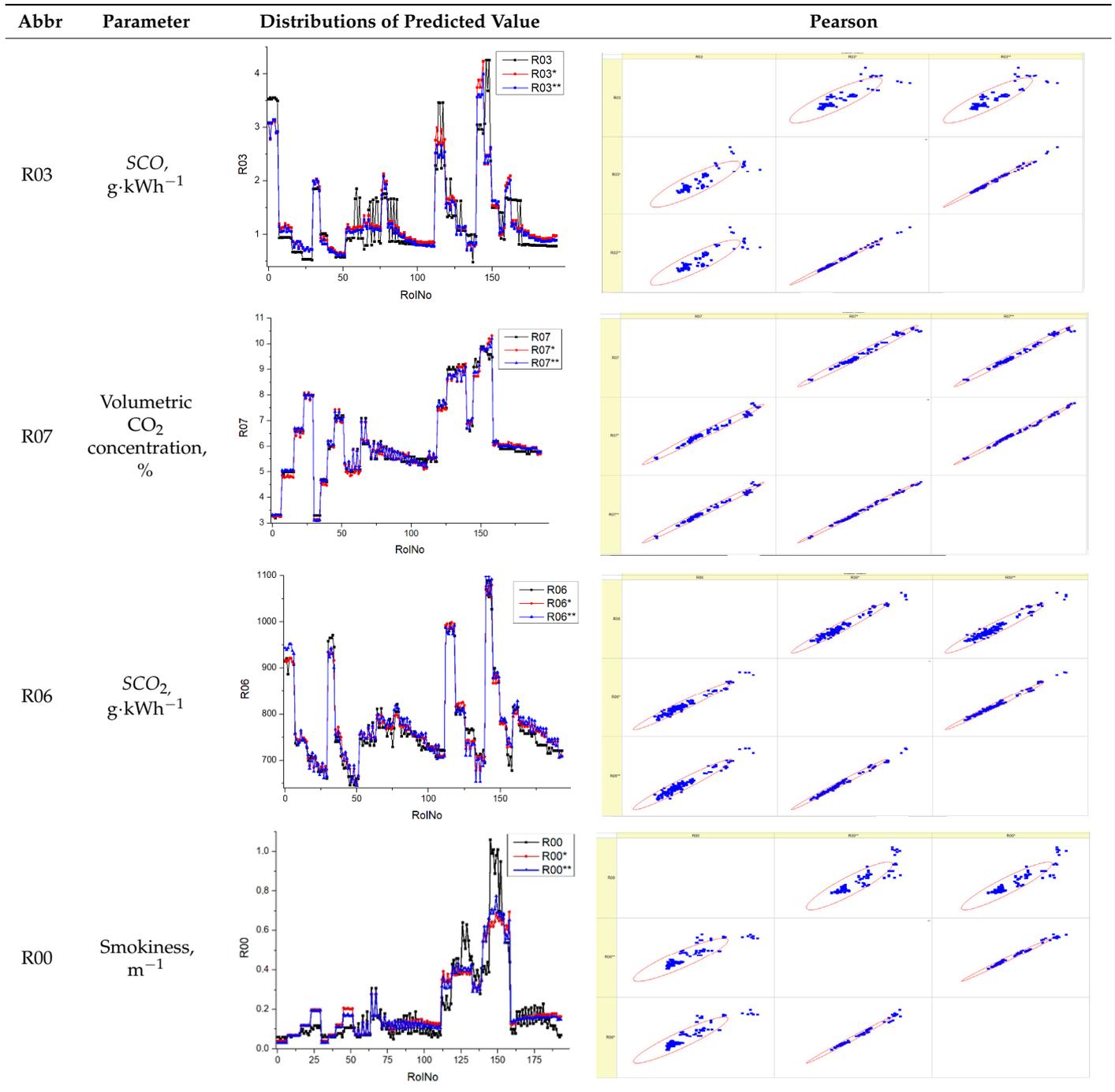


Table 11. Cont.

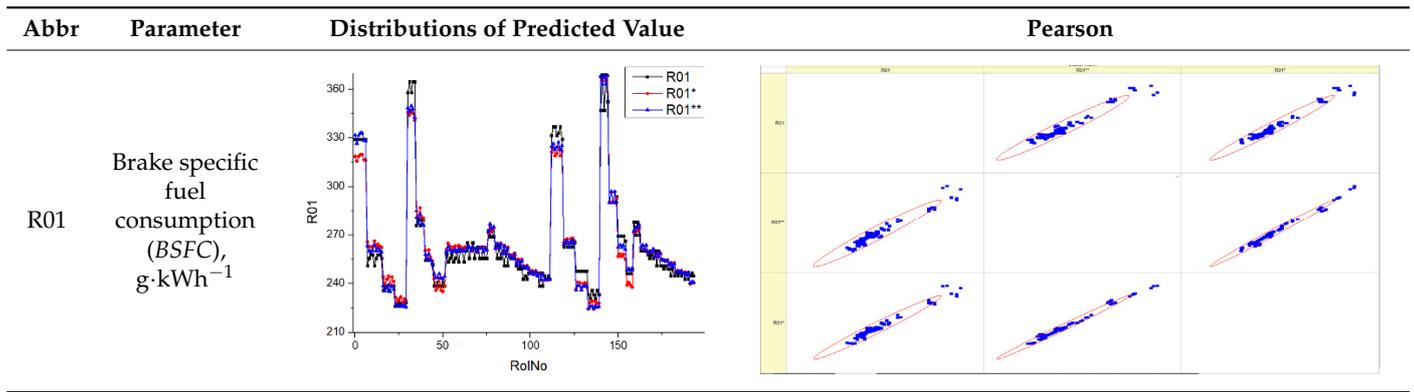


Table 12. Results of validation after training of ANNs (one hidden layer, $M = 1000$). Distributions of predicted values R02, R05, R08, R04, and R09 and corresponding Pearson diagrams. Two different training routines T5 and T6 were used (see Table 5). Number of training epochs: 1,000,000. Distributions of values: R as real experimental value, R* as predicted using the T5 routine, and R** as predicted using the T6 routine. Number of events for validation 194.

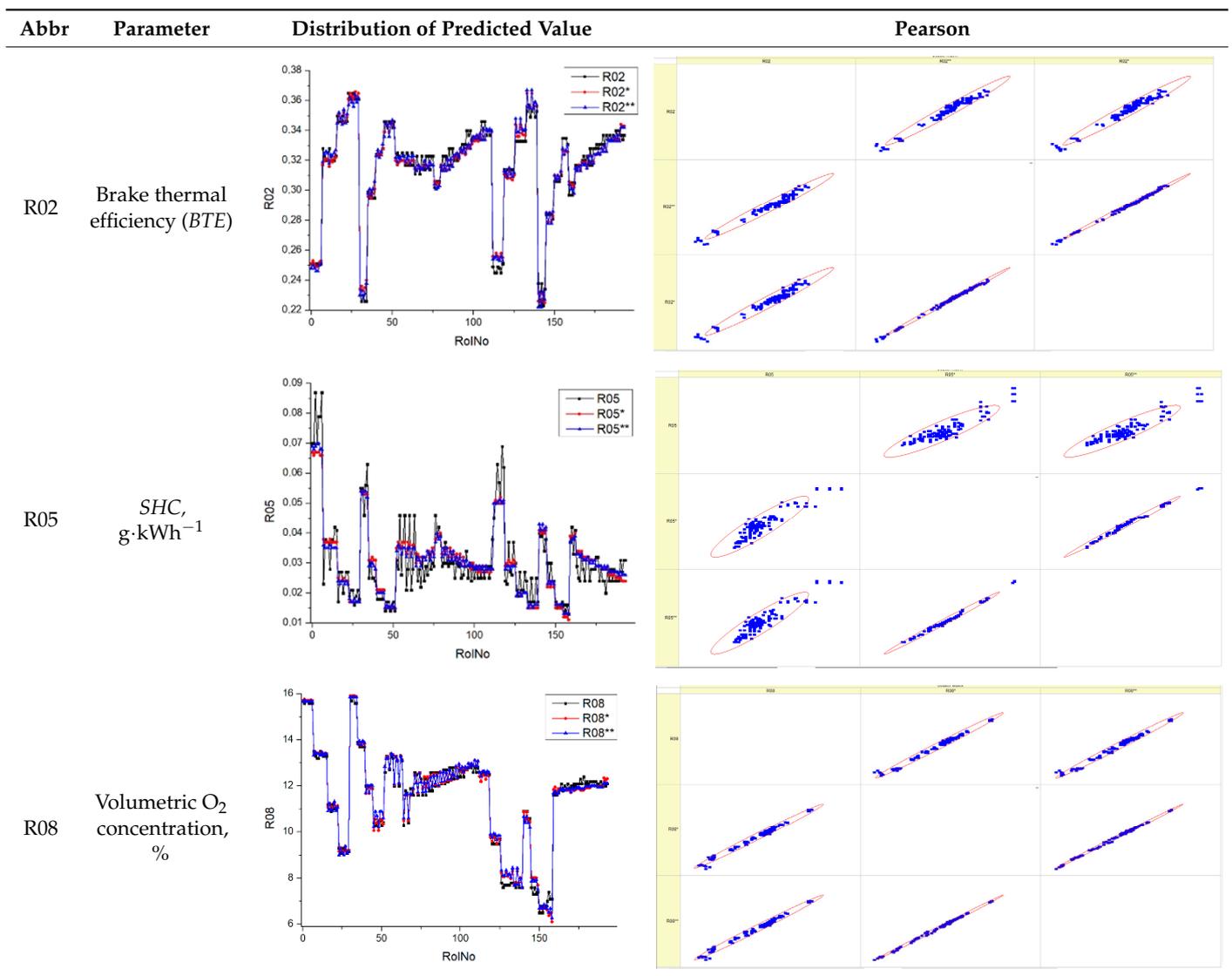


Table 12. Cont.

Abbr	Parameter	Distribution of Predicted Value	Pearson
R04	$SNO_x, g \cdot kWh^{-1}$		
R09	Volumetric NO_x concentration, ppm		

4. Discussion

The performance of ANNs is heavily dependent on the architecture and dynamic training mode. Three different stages were overcome to achieve a good result.

The first stage was related to the selection of interfaces. The output parameters (given in Table 4) are the measurement parameters that are appropriate to use for emission assessment. The number of output units for ANNs ($N = 10$) was established according to the experimental setup (R00...R09; see Table 4). For input parameters, two problems occur at the initial simulation. Firstly, we decided to use a significantly lower number of input parameters ($L = 8$). Parameters P00...P07 are traditional parameters that are suitable for the description of different power regimes of diesel engines (see Table 3). Unfortunately, the ANN learning process was unsuccessful. Then, we decided to increase the number of input units ($L = 12$) by adding several technical and physical parameters P08...P11 step-by-step, which allowed for receiving a satisfactory process of ANN learning. Secondly, the clusterization of input parameters needed realized using several technical and physical approaches. We decided to create the first input cluster according to the technical suggestions (P10, P03, P02, P11, and P01) and the second cluster according to the burning chemistry suggestions (P04, P05, P12, P06, P08, and P07). This assumption allows us to significantly improve the ANN learning process and avoid unpredictable increases in TNE.

The second stage pertains to the selection of the artificial neural network architecture. The feedforward method (information flow from the input layer through hidden layers to the output layer) was chosen due to the cause-and-effect relationship [37]. The possibility of using an ANN containing a single-hidden layer and multi-hidden layers was discovered and estimated. ANNs with double-hidden layers and triple-hidden layers are suitable for complex data containing hierarchical features. Generally, training an ANN with double- or triple-hidden layers is easier than with a single-hidden layer because fewer parameters require optimization. In our case, hierarchical-related data are absent. To decrease the wasting of computer resources (to decrease the training time), we decided to use the ANN containing a single-hidden layer due to the absence of multistep hierarchical behavior (see

Tables 3 and 4). The amount of perceptrons per hidden layer plays a crucial role in the training process. There is no general rule for the size of the hidden layer, but there are some empirical formulas. For example, Bekešienė et al. [27] presented some formulas for the expression of the size of the hidden layer (in our case, it would be $M = 20 \dots 50$). The decision was to increase M significantly per order and more by up to 500 and 1000. The regime of overfitting was exceeded at $M = 2000$. Due to that, the amount of perceptrons in the single-hidden layer must be in intervals (500; 1000). Bias was presented for adjusting purposes, but finally, we did not use this possibility to shift the argument of the action function sigmoid.

The third stage represents the training process. In the case of the single-hidden layer, we increased the starting number of training epochs (50,000) to 500,000 and 1,000,000, which allowed us to significantly improve the result. According to the distributions of TNE (see Figure 4), modes T5 and T6 must be named as satisfied. The quality of training could be established using the TNE parameter (see Equation (12)) or gradient distribution. We have used the TNE distribution, which allows us to assess the overtraining state and the unlearning state (both of which are indicators of incomplete training).

There were classifications for assessing the quality of ANN predictions as both a science and a kind of art. The quality of predictions is related to the training process, and the quantitative dynamical parameters of the training process determine further validation and prediction. The first approach to estimating the training process could be conducted using the TNE distribution (Figure 5). There was an exponential decrease in TNE as the number of epochs increased, which allowed the learning process to be called satisfied. In the interval from 500,000 to 1,000,000 epochs, the overtraining state was not distinguished (no significant increase in TNE distribution, more than two orders of magnitude or more). The second approach to estimating the training process is related to the existence of a *plateau* phase (i.e., saturation of the TNE distribution). In this case, this regime was distinguished after 100,000 epochs only (see Table 6).

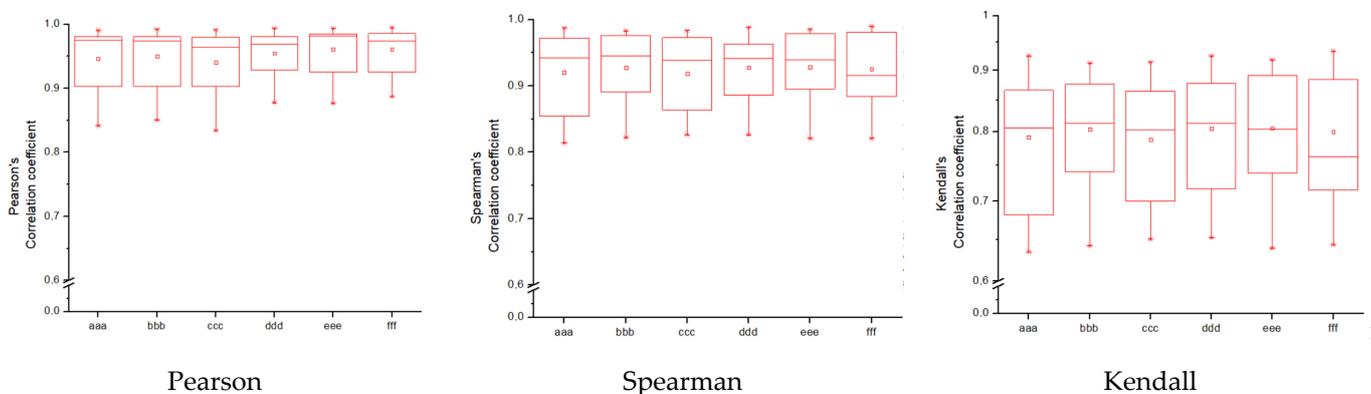


Figure 5. Comparison of different statistics: Pearson, Spearman, and Kendall.

Generally, it is impossible to evaluate which parameters have a less sensible result. The quality of training could be established using the TNE parameter (see Equation (12)) or gradient distribution. We have used TNE distribution, which allows us to assess the overtraining state (which is out of our interest). We have used several sets of input interfaces with different numbers of parameters ($L = 7, 8, 10$, and 12). Only one expanded set (P01–P12, $L = 12$; see Table 3) allows for a successful process of training. The possibility of removing several parameters from the expanded set (P01–P12, $L = 12$) was checked, but no significant training process was established.

The results in Tables 7–12 can be used for a nondirected sensitivity analysis. This is possible when validation is shown along with Pearson distributions after training an ANN using different training regimes. The used ANN (feedforward ANN, two adjusted input, output interfaces, architecture of ANN (single-hidden layer, $M = 500$ and $M = 1000$) and

dynamical regime—number of epochs 500,000 or 1,000,000)) allows to receive very high agreement between experimental and predicted results (R and R*, R and R**).

After evaluating the distributions of predicted values (Tables 7–12), it is necessary to pay attention to the best prediction found for the first cluster: volumetric O₂ concentration (R08), SNO_x (R04), the volumetric concentration of NO_x (R09), and SHC (R05). The third cluster contains SCO (R03), volumetric CO₂ concentration (R07), and SCO₂ (R06). The predictions of both clusters are in good agreement with the experimental ones.

The second cluster contains smoke (R00), brake specific fuel consumption (BSFC) (R01), and brake thermal efficiency (BTE) (R02). Especially for smoking, the predicted values are far from the experimental values. This large difference can be explained by measurement error (the effect of contaminant coupling in outcome tubes). A large deviation of smokiness (R00) between experimental and predicted values is essential when the V stage (regimes 24–27, 113–140) and the VI stage (regimes 28–31, 141–159) are distinguished. In all cases, extreme conditions (engine speed was set at 2500 rpm and the load was set at 30 Nm, 60 Nm, 90 Nm, and 120 N) have a bad correlation with the output parameter smokiness.

Figure 5 represents a comparison of different statistics: Pearson, Spearman, and Kendall.

Pearson, Spearman, and Kendall correlations were used to assess the magnitude and orientation of associations among variables. Figure 5 illustrates that the data dependencies exhibit a more linear pattern. As the number of epochs grows, the range of data quantiles reduces, resulting in a more condensed distribution. This is true for both the whole data package and the average data package, as demonstrated by the Pearson correlation. The Spearman correlation coefficient assists in comprehending the monotonic relationship of the data. It is evident that the data exhibited essentially identical variations while increasing the number of epochs and when analyzing the full and average data packets. The analyzed data is likely non-monotonic. Kendall's correlation coefficient enables us to assess the degree of non-linearity in the data. Both Pearson and Kendall correlations demonstrate that the relationships in our dataset are linear in nature.

Commonly used statistical distributions show an exact and close-to-exact agreement between the experimental values and the expected ones. Pearson coefficient deviations are in the interval (3; 10%) (see Table 5). There were precise value predictions for the R00 (smokiness) distribution. The use of two training modes (500,000 and 1,000,000 epochs) and different ANN architectures (number of perceptrons 500 and 1000) cannot improve the result (RolNo110–130, 140–160, see Table 9, row R00 Smokiness). Perhaps the training data set for the R00 distribution (smokiness) is incomplete and requires partial experimental correlation. This hypothesis was made because only a few confirmed values deviated significantly from the experimental range. Evaluation of experimental regimes represents extreme engine operating conditions, and inaccurate predictions occur only at extreme regimes. Stage V (Modes 24–27, Rol No 110–130) was set at 2500 rpm, with a load of 90 Nm and 120 Nm. For stage VI (Modes 28–31, 140–159), the engine speed was set at 2500 rpm and the load was 60 Nm, 90 Nm, and 120 Nm. All series of experiments include the loads of 30, 60, 90, and 120 Nm. Two solutions to the presented problem could be formulated. Firstly, for extreme regimes, an incomplete set of input parameters must be supplemented by one or several parameters that allow the specified behavior of complex and complicated burning processes. Secondly, the experimental data set for training operations must be significantly increased, especially when using extreme regimes.

Other distributions (for example, R05 and SHC, see Table 12) show a close-to-satisfied agreement between the predicted values and the experimental ones. The R05 presents the experimental values in a chaotic manner, and the ANN prediction's performance functions as a filter, averaging the weight.

5. Conclusions

1. The advanced tool VALLUM01 (with ANN implementation) containing a user-friendly interface for data input and output facilities was created, designed, and tested to pro-

vide simulations and predictions of exhausts in motor outcomes. A user-friendly input/output interface was created and used for solving the specific task of diesel motor efficiency using ANN. The set of input parameters (12) and output parameters (10) was estimated to be significant and sufficient for training, validation, and prediction. Intervals of values were recognized as suitable for fuzzification for input/output to ANN.

2. Training sessions for ANN (1,000,000 epochs, 1000 perceptrons in a single-hidden layer) could be titled as the most successful. For training, the use of averaged values instead of real experimental values is acceptable.
3. Following the development of a user-friendly input/output interface, the appropriateness of the input values for the artificial neural network (ANN) was verified (Table 3).
4. The first cluster, which includes volumetric O₂ concentration, SNO_x, and SHC, and the third cluster, which includes SCO, CO₂ concentration, and SCO₂, yielded the best predictions. However, the second cluster, including smoke, brake specific fuel consumption, and brake thermal efficiency, showed significant deviations from experimental values, mainly due to measurement error and extreme conditions.

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Abbreviations

λ	The excess air ratio
AI	Artificial intelligence
ANN	Artificial neural networks
BMEP	Brake mean effective pressure
BTE	Brake thermal efficiency
BSFC	Brake specific fuel consumption
CO ₂	Carbon dioxide
CO	Carbon monoxide
D100	Pure fossil diesel fuel
ECU	Engine control unit
EGR	Exhaust gas recirculation
HC	Hydrocarbons
HVO100	Hydrotreated Vegetable Oil
l_0	Stoichiometric air to fuel ratio
LHV	Lower heating value
ML	Machine Learning
MLP	Multilayer perceptron
MLPNN	Multilayer perceptron neural network
NO _x	Nitrogen oxides
RSM	Response surface methodology
SCO ₂	Recalculated CO ₂ value
SCO	Recalculated CO value
SHC	Recalculated HC value

SO	Smoke opacity
SOI	Start of injection
SNO _x	Recalculated NO _x value
TNE	Total network error
H ₂ O	Water

References

- Ulbrich, D.; Selech, J.; Kowalczyk, J.; Józwiak, J.; Durczak, K.; Gil, L.; Pieniak, D.; Paczkowska, M.; Przystupa, K. Reliability Analysis for Unrepairable Automotive Components. *Materials* **2021**, *14*, 7014. [CrossRef]
- Oulmelk, A.; Sрати, M.; Afraites, L.; Hadri, A. An Artificial Neural Network Approach to Identify the Parameter in a Nonlinear Subdiffusion Model. *Commun. Nonlinear Sci. Numer. Simul.* **2023**, *125*, 107413. [CrossRef]
- Borucka, A.; Kozłowski, E.; Antosz, K.; Parczewski, R. A New Approach to Production Process Capability Assessment for Non-Normal Data. *Appl. Sci.* **2023**, *13*, 6721. [CrossRef]
- Žvirblis, T.; Hunicz, J.; Matijošius, J.; Rimkus, A.; Kilikevičius, A.; Gęca, M. Improving Diesel Engine Reliability Using an Optimal Prognostic Model to Predict Diesel Engine Emissions and Performance Using Pure Diesel and Hydrogenated Vegetable Oil. *Eksploat. I Niezawodn.–Maint. Reliab.* **2023**, *25*, 174358. [CrossRef]
- Sindhu, T.N.; Çolak, A.B.; Lone, S.A.; Shafiq, A.; Abushal, T.A. A Decreasing Failure Rate Model with a Novel Approach to Enhance the Artificial Neural Network's Structure for Engineering and Disease Data Analysis. *Tribol. Int.* **2023**, *192*, 109231. [CrossRef]
- Alam, M.S.; Deb, J.B.; Amin, A.A.; Chowdhury, S. An Artificial Neural Network for Predicting Air Traffic Demand Based on Socio-Economic Parameters. *Decis. Anal. J.* **2024**, *10*, 100382. [CrossRef]
- AlAlaween, W.H.; Mahfouf, M.; Omar, C.; Al-Asady, R.B.; Monaco, D.; Salman, A.D. Serial Artificial Neural Networks Characterized by Gaussian Mixture for the Modelling of the Consigma25 Continuous Manufacturing Line. *Powder Technol.* **2024**, *434*, 119296. [CrossRef]
- Soori, M.; Arezoo, B.; Dastres, R. Artificial Neural Networks in Supply Chain Management, a Review. *J. Econ. Technol.* **2023**, *1*, 179–196. [CrossRef]
- Adedeji, B.P. Electric Vehicles Survey and a Multifunctional Artificial Neural Network for Predicting Energy Consumption in All-Electric Vehicles. *Results Eng.* **2023**, *19*, 101283. [CrossRef]
- Sahin, G.; Isik, G.; van Sark, W.G.J.H.M. Predictive Modeling of PV Solar Power Plant Efficiency Considering Weather Conditions: A Comparative Analysis of Artificial Neural Networks and Multiple Linear Regression. *Energy Rep.* **2023**, *10*, 2837–2849. [CrossRef]
- Zurada, J.M. *Introduction to Artificial Neural Systems*; West: St. Paul, MN, USA, 1992; ISBN 978-0-314-93391-1.
- Rabunal, J.R.; Dorado, J. (Eds.) *Artificial Neural Networks in Real-Life Applications*; Idea Group Pub: Hershey, PA, USA, 2006; ISBN 978-1-59140-902-1.
- Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*. Available online: <https://www.deeplearningbook.org/> (accessed on 31 December 2023).
- Torres Sospedra, J. *Ensembles of Artificial Neural Networks: Analysis and Development of Design Methods*; Universitat Jaume I. Departament d'Enginyeria i Ciència dels Computadors: Castellon, Spain, 2011.
- Lou, C. *Artificial Neural Networks: Their Training Process and Applications*; Department of Mathematics Whitman College: Walla Walla, WA, USA, 2019.
- Li, R.; Herreros, J.M.; Tsolakis, A.; Yang, W. Integrated Machine Learning-Quantitative Structure Property Relationship (ML-QSPR) and Chemical Kinetics for High Throughput Fuel Screening toward Internal Combustion Engine. *Fuel* **2022**, *307*, 121908. [CrossRef]
- Ahmad, I.; Sana, A.; Kano, M.; Cheema, I.I.; Menezes, B.C.; Shahzad, J.; Ullah, Z.; Khan, M.; Habib, A. Machine Learning Applications in Biofuels' Life Cycle: Soil, Feedstock, Production, Consumption, and Emissions. *Energies* **2021**, *14*, 5072. [CrossRef]
- Usman, M.; Jamil, M.K.; Ashraf, W.M.; Saqib, S.; Ahmad, T.; Fouad, Y.; Raza, H.; Ashfaq, U.; Pervaiz, A. AI-Driven Optimization of Ethanol-Powered Internal Combustion Engines in Alignment with Multiple SDGs: A Sustainable Energy Transition. *Energy Convers. Manag. X* **2023**, *20*, 100438. [CrossRef]
- Deng, Jiamei; Stobart; Richard; Basti, M. The Applications of Artificial Neural Networks to Engines. In *Artificial Neural Networks-Industrial and Control Engineering Applications*; Suzuki, K., Ed.; InTech: Vienna, Austria, 2011; ISBN 978-953-307-220-3.
- Xing, Y.; Zheng, Z.; Sun, Y.; Agha Alikhani, M. A Review on Machine Learning Application in Biodiesel Production Studies. *Int. J. Chem. Eng.* **2021**, *2021*, 2154258. [CrossRef]
- Aliramezani, M.; Koch, C.R.; Shahbakhti, M. Modeling, Diagnostics, Optimization, and Control of Internal Combustion Engines via Modern Machine Learning Techniques: A Review and Future Directions. *Prog. Energy Combust. Sci.* **2022**, *88*, 100967. [CrossRef]
- Zhang, L.; Zhu, G.; Chao, Y.; Chen, L.; Ghanbari, A. Simultaneous Prediction of CO₂, CO, and NO_x Emissions of Biodiesel-Hydrogen Blend Combustion in Compression Ignition Engines by Supervised Machine Learning Tools. *Energy* **2023**, *282*, 128972. [CrossRef]

23. Khac, H.N.; Modabberian, A.; Zenger, K.; Niskanen, K.; West, A.; Zhang, Y.; Silvola, E.; Lendormy, E.; Storm, X.; Mikulski, M. Machine Learning Methods for Emissions Prediction in Combustion Engines with Multiple Cylinders. *IFAC-PapersOnLine* **2023**, *56*, 3072–3078. [[CrossRef](#)]
24. Venkatesh, S.N.; V, S.; Thangavel, V.; Balaji P, A.; Vijayaragavan, M.; Subramanian, B.; Josephin JS, F.; Varuvel, E.G. Efficacy of Machine Learning Algorithms in Estimating Emissions in a Dual Fuel Compression Ignition Engine Operating on Hydrogen and Diesel. *Int. J. Hydrogen Energy* **2023**, *48*, 39599–39611. [[CrossRef](#)]
25. Lionus Leo, G.M.; Jayabal, R.; Srinivasan, D.; Chrispin Das, M.; Ganesh, M.; Gavaskar, T. Predicting the Performance and Emissions of an HCCI-DI Engine Powered by Waste Cooking Oil Biodiesel with Al₂O₃ and FeCl₃ Nano Additives and Gasoline Injection—A Random Forest Machine Learning Approach. *Fuel* **2024**, *357*, 129914. [[CrossRef](#)]
26. Williams, Z.; Moiz, A.; Cung, K.; Smith, M.; Briggs, T.; Bitsis, C.; Miwa, J. Generation of Rate-of-Injection (ROI) Profile for Computational Fluid Dynamics (CFD) Model of Internal Combustion Engine (ICE) Using Machine Learning. *Energy AI* **2022**, *8*, 100148. [[CrossRef](#)]
27. Bekesiene, S.; Smaliukiene, R.; Vaicaitiene, R. Using Artificial Neural Networks in Predicting the Level of Stress among Military Conscripts. *Mathematics* **2021**, *9*, 626. [[CrossRef](#)]
28. Jovanović, N.; Vasović, B.; Jovanović, Z.; Cvjetković, M. Neural Network Implementation in Java. *Bizinfo* **2020**, *11*, 19–30. [[CrossRef](#)]
29. Godwin, D.J.; Varuvel, E.G.; Martin, M.L.J. Prediction of Combustion, Performance, and Emission Parameters of Ethanol Powered Spark Ignition Engine Using Ensemble Least Squares Boosting Machine Learning Algorithms. *J. Clean. Prod.* **2023**, *421*, 138401. [[CrossRef](#)]
30. Valeika, G.; Matijošius, J.; Górski, K.; Rimkus, A.; Smigins, R. A Study of Energy and Environmental Parameters of a Diesel Engine Running on Hydrogenated Vegetable Oil (HVO) with Addition of Biobutanol and Castor Oil. *Energies* **2021**, *14*, 3939. [[CrossRef](#)]
31. Rimkus, A.; Žaglinskis, J.; Stravinskas, S.; Rapalis, P.; Matijošius, J.; Bereczky, Á. Research on the Combustion, Energy and Emission Parameters of Various Concentration Blends of Hydrotreated Vegetable Oil Biofuel and Diesel Fuel in a Compression-Ignition Engine. *Energies* **2019**, *12*, 2978. [[CrossRef](#)]
32. Shepel, O.; Matijošius, J.; Rimkus, A.; Duda, K.; Mikulski, M. Research of Parameters of a Compression Ignition Engine Using Various Fuel Mixtures of Hydrotreated Vegetable Oil (HVO) and Fatty Acid Esters (FAE). *Energies* **2021**, *14*, 3077. [[CrossRef](#)]
33. Ross-Tech: Home. Available online: <https://www.ross-tech.com/index.php> (accessed on 31 December 2023).
34. Heywood, J.B. *Internal Combustion Engine Fundamentals*, 2nd ed.; McGraw-Hill Education: New York, NY, USA, 2018; ISBN 978-1-260-11610-6.
35. Gruodis, A. VALLUM01. Advanced Tool for Implementation of Artificial Neural Network Containing Tabular Interface for Input/Output 2023. Available online: <https://github.com/solo51/VALLUM> (accessed on 31 December 2023).
36. Sonawane, S. Understanding and Implementing Neural Networks in Java from Scratch. Available online: <https://towardsdatascience.com/understanding-and-implementing-neural-networks-in-java-from-scratch-61421bb6352c> (accessed on 31 December 2023).
37. Gruodis, A. Realizations of the Artificial Neural Network for Process Modeling. Overview of Current Implementations. *Appl. Bus. Issues Solut.* **2023**, *2*, 22–27. [[CrossRef](#)]

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