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Prediction of CO emission from I. C. Engines using Back Propagation Neural Network

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Abstract: *Environmental pollution is a great hazard to our eco-system which is also being adversely affected by emissions from internal combustion (I.C.) engines. In the present work, an attempt has been made towards the application of Back Propagation Neural Network (BPNN) for predicting the CO emission from a diesel engine so that better control of the engine parameters may be performed to minimize the level of emission. The data collected for training the Neural Network (NN) were compression ratio, injection timing, load, cylinder peak pressure, crank angle at peak pressure, temperature of cooling water, and temperature of exhaust gas. It has been observed that by the selective combination of input parameters to the NN may effectively predict the level of CO emission with minimum RMS error for effective control of emission.*

Keywords: *Emission, Back propagation neural network (BPNN), Neural Network (NN), RMS error*

I. Introduction

Automotive pollution is one of the banes of the modern society because the exhaust emissions from them degrade the environment. The emissions from an internal combustion (I.C.) engine have the adverse affect on human health as well as the plant kingdom. With the increase in the number of vehicles, the pollutants such as hydrocarbons (HC), nitrogen- oxides (NO_x), Carbon monoxide (CO) and particulate matter (PM) have been increasing at an alarming rate. After years of research, there is a drastic change of technology which has converted the conventional I.C. engines into electronically controlled vehicles. The drastic development in computer technology and sensor systems has made it possible to achieve better control over the pollutants. Yet the concept of green vehicle in ideal sense is a dream of the future because the thrust of the research is towards the development of intelligent vehicle with decision making capability. One such direction is the application of artificial neural network in I.C. engine systems, as it has various capabilities such as self learning, parallel & distributed processing and very large scale integration (VLSI) system implementation. Due to such attributes, Artificial Neural Network (ANN) has attracted the attention of the researchers in the recent times for application in I.C. engine technology. With the use of ANN, it may become possible to predict these emissions quite close to their actual values and hence better control may be achieved for implementation.

Artificial Neural Network (ANN) is general term representing the model of human brain and its processing, developed by soft computing practitioners. Among its various types, one of the most popular techniques followed is back-propagation neural network (BPNN). This neural network is given example sets of data as inputs obtained from practical results, for example, from the data obtained during experiments in a diesel engine test rig by using various settings of the engine and observing the CO emission results at the exhaust. The algorithm of BPNN requires repeated iterations to be performed with the same sets of data so that the network produces calculated results of emission by using its algorithm, which are called predicted results of emission. These predicted results will be different, naturally to some extent, from the actual result of emission during the experiment and thus the RMS error may be calculated. This error is used during the iterations for improving the results of prediction and the name of back propagation comes from this fact.

The aim of the research is to study the architecture and algorithm for the Back Propagation Neural Network (BPNN) and its features, to plan and strategise the data collected from a stationary diesel engine with sensors for subsequent use in BPNN and to examine the applicability of BPNN architecture of ANN in predicting the CO emission of I.C. engines.

II. Previous Research

Through some of the research works undertaken by various scientists from time to time, it is evident that ANN has been successfully applied to predict the emission of an I.C. engine. A survey is undertaken on the papers published by the research workers:

Karakitsios et.al (2005) made an attempt based on vehicle speed and vehicle's category traffic flow as inputs, to develop NN model and it with back propagation algorithm to calculate the emissions of CO, C_6H_6, NO_x and PM_{10} and the corresponding error (calculated v/s observed values) was lower than 3% in a complex busy avenue environment[1].

Obodeh et.al (2009) carried out experiments with a light duty Nissan diesel engine test rig to measure engine operating parameters and its tail pipe emissions. ANN's were trained on experimental data using Levenberg-Marquardt (LM) algorithm in different architectures of back propagation to predict the oxides of nitrogen (NO_x) emissions under various operating variables. For pre-specified engine speeds and loads with LM algorithm, absolute percentage errors were found between 0.68% to 3.34%[2].

M.Ali Akcayol et. al (2005) made an attempt to improve cold start performance of catalytic converters for HC and CO emissions with the help of a burner heated catalyst tested in a four stroke spark ignition engine using back propagation learning algorithms of ANN for prediction of catalyst temperature, CO and HC emissions. The training dataset was taken from experiment. it was found that the deviation coefficients for standard and heated catalyst temperature are less than 4.925%,and 1.602%, the same for standard and heated catalyst HC emissions are less than 4.798% and 4.926% and that for standard and heated catalyst CO emissions are less than 4.82% and 4.938% respectively[3].

Shivakumar et.al (2010) used Artificial neural networks (ANN's) to predict the engine performance and emission characteristics of a single cylinder, four stroke, and water cooled compression ignition engine using blends of Hunge oil with diesel at various compression ratios as fuel. The ANN was trained with back propagation algorithm using compression ratio, blend percentage and percentage load as input variables whereas performance parameters together with engine exhaust emissions were used as output variables. ANN showed good convergence between predicted and experimental values for various performance parameters and emissions with mean squared error closed to 1 and mean relative error less 9%[4].

III. Research Method

The entire experiment was carried out at the I.C. Engine laboratory in a **computerized single cylinder, four stroke, multi-fuel, variable compression ratio (VCR) engine**. The fuel used for the experiment was **high speed diesel.** The setup consists of single cylinder, four stroke, multi-fuel, research engine connected to eddy current type dynamometer for loading. The operation mode of the engine can be changed from Diesel to Petrol and vice versa. In both the modes, the compression ratio can be varied without stopping the engine and without altering the combustion chamber geometry by a specially designed *tilting cylinder block* arrangement. The injection point and spark point can be changed for research tests. Setup is provided with necessary instruments for measuring combustion pressure, diesel line pressure and crank-angle. These signals are interfaced with computer for pressure crank-angle diagrams. Instruments are provided to interface airflow, fuel flow, temperatures and load measurements.

Table 1: Engine Specifications

MAKE	KIRLOSKAR	
MODEL	TV1	
Stroke	110 mm	
Bore	87.5 mm	
Capacity	661 cc.	
Diesel mode	**Power**	3.5 KW
	Speed	1500 rpm
	CR range	12:1-18:1
	Injection variation	0-25Deg BTDC

Table1: Engine specifications (Contd.)

Petrol mode	**Power**	4.5 KW @ 1800 rpm
	Speed range	1200-1800 rpm
	CR range	6:1-10:1
	Spark variation	0-70 deg BTDC
Fuel tank	**Capacity**	15 lit
	Type	Duel compartment, with fuel metering pipe of glass

Table 2: Instrumentation for Measurement

Dynamometer Type	Eddy current, water cooled, with loading unit
MAKE	SAJ TEST PLANT PVT.LTD
MODEL	AG10
Propeller shaft	With universal joints
MAKE	HIDUSTAN HARDY SPICER
MODEL	1260
Air box	MS fabricated with orifice meter and manometer
Calorimeter Type	Pipe in pipe
Crank angle sensor **MAKE:** KUBLER-GERMANY	Dia: 37mm, Shaft Size: Size 6mmxLength 12.5mm, Supply Voltage: 5-30V DC

MODEL: 8.3700.1321.0360	**Resolution**	1 Deg
	Speed	5500 RPM with TDC pulse
Data acquisition device	**NATIONAL INSTRUMENTS USB**	6210, 16-bit, 250kS/s
Piezo powering unit	**MAKE**	Cuadra
	MODEL	AX-409
Digital voltmeter **MAKE:** Meco **MODEL:** SMP35	**Range**	0-20V
	Panel	Mounted
Temperature sensor **MAKE:** Radix	**Type**	RTD, PT100
	Thermocouple	Type K
Load indicator **MAKE:** Selectron **MODEL:** PIC152	**Range**	0-50 Kg
	Supply	230VAC

Table 2 Instrumentation for Measurement (Contd.)

Load sensor	**Type**	Strain gauge
	Range	0-50 Kg
	MAKE **MODEL**	Sensotronics Sanmar Ltd. 60001
Fuel flow transmitter	**MAKE** **MODEL**	Yokogawa EJA110-EMS-5A-92NN
	Range	0-500 mm WC

Data on exhaust emission were collected by varying the controllable parameters of the engine among which are Compression Ratio (CR), Injection Timing (IT) and Load (W) on the engine are crucial. They are used to design the experiments to study the CO emission behaviour from the engine and also to record the parameters such as observed load (W_{OBS}), water inlet and outlet temperature to and from the engine respectively (T_1 & T_2) engine exhaust temperature (T_5) from calorimeter, peak cylinder pressure (P.P), crank angle corresponding to peak pressure (θ_{peak}), indicated air pressure in mm of water column in the calorimeter(Air pr.) and rate of fuel into the cylinder(R.F.I).

Altogether sixty three experiments were conducted by making CR (3 levels), IT (3 levels) and W (7 levels), i.e. Full Factorial = 3 x 3 x 7 = 63

III. (A) Artificial Neural Networks Modelling

The present research uses BPNN where McCulloch Pitts model of artificial neuron is used shown in Fig.1 below.

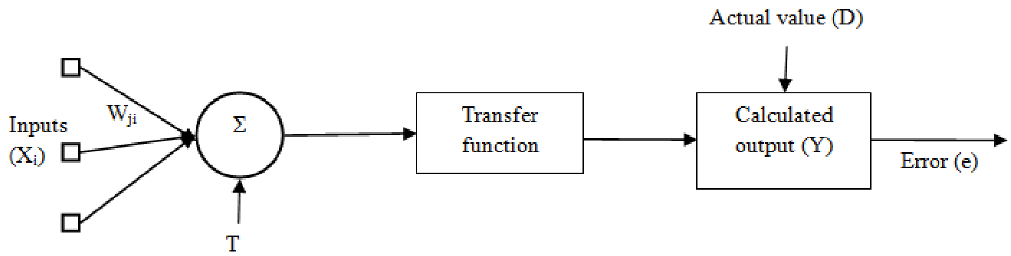

Fig. 1 Mcculloch Pitts Model of Artificial Neuron (Also Called Perceptron)

X_1, X_2 and X_3 = Inputs, W_1, W_1 and W_3 = Synaptic weights, T = Threshold

Transfer function: Examples are Sigmoid, Hyperbolic tangent etc.

Σ = summing junction

Information Processing

Weighted sum (V) = $W_1.X_1 + W_2.X_2 + W_3.X_3 – T$, for i=1, 3, j = 1, 3

Now the neuron *fires* only when V≥0 and gives the output, generally using Sigmoid function (shown below); otherwise the output = 0.0

$$\text{Output (Y)} = \frac{1}{1+e^{-V}} \qquad (1)$$

III. (B) Back Propagation Neural Network (BPNN) Architecture

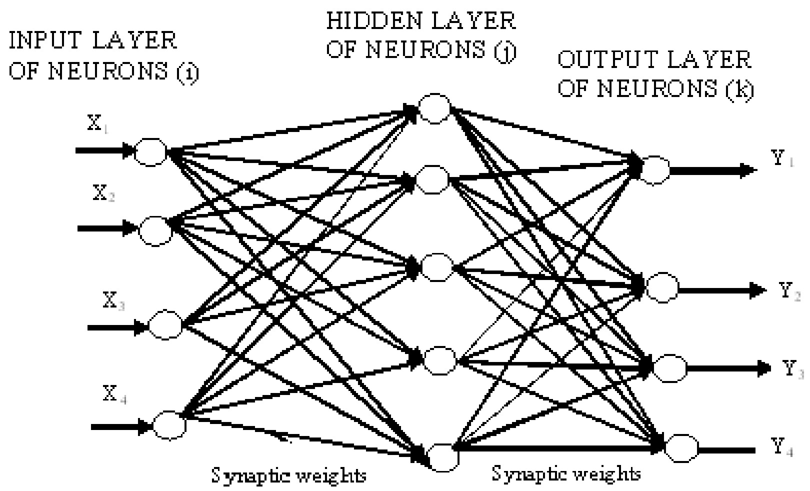

Fig2. BPNN Architecture

This type of network shown in Fig. 2 is sometimes called multilayer perception (MLP) because of its similarity to perception networks with more than one layer. The network consists of a number of layers called the input, hidden and output layers. The hidden and output layers contain a number of neurons or processing elements which are connected by links or connections to show the flow direction of signals and also to represent weight or strength of their respective connections. In an MLP of the back propagation type, the connections are first initialized by a set of uniformly distributed random numbers between 0 and 1.

The calculations are made in feed forward manner until back propagation of errors is done.
Following the processing in a single neuron (Fig. 1), outputs from the neurons of a certain layer (eq. 1) are given as inputs to the neurons of the next layer.
Finally the output layer gives the calculated output (Y_K) from the BPNN and the back propagation begins on the basis of prediction error (e_K).
The flow chart shown in Fig. 3 summarizes the operation of BPNN:

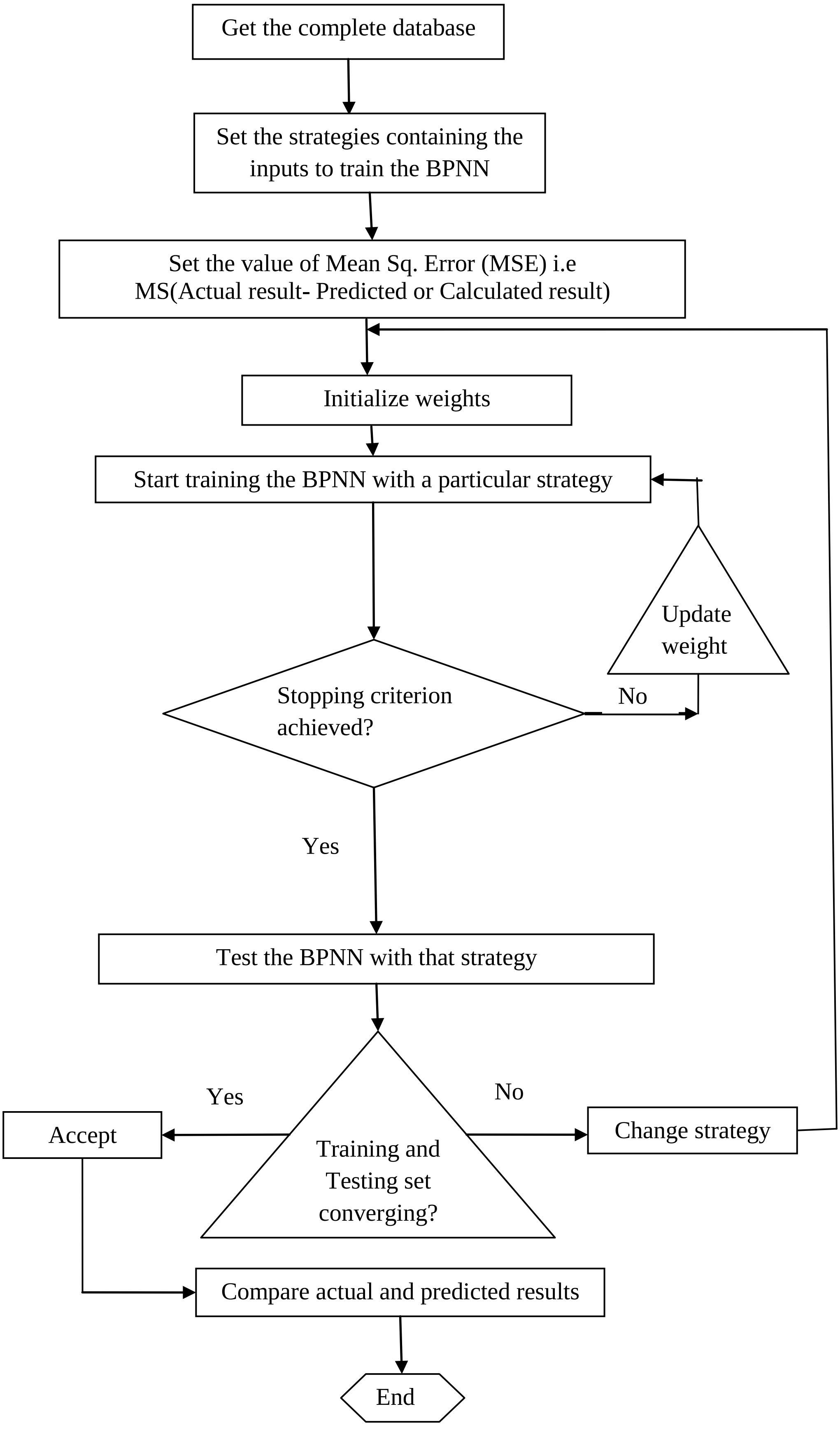

Fig.3 Flow chart of BPNN

The errors are:

RMS training error = $\sqrt{\frac{1}{2(NTR)}\sum_{n=1}^{NTR}\sum_{j\epsilon C}[d_K^{TR}(n) - Y_K^{TR}(n)]^2}$ (2)

RMS testing error = $\sqrt{\frac{1}{2(NTS)}\sum_{n=1}^{NTS}\sum_{j\epsilon C}[d_K^{TS}(n) - Y_K^{TS}(n)]^2}$ (3)

TR = training set, TS = testing set, NTR = no. of training set, NTS = no. of testing set,
C = no. of output nodes.

The iterations may be stopped for any of the following reasons:

(a) Either after a certain number of iterations
(b) Or after a desired precision level is achieved
(c) Or the RMS Testing error begins to increase (called Over learning/Over training) shown next [5]

III. (C) Strategic Analysis

The entire set of 63 data is divided into 42 nos. of training set and 21 nos. of testing set. The performance of the various input parameters for predicting the output (CO emission from the engine) are studied with the help of BPNN program. For this purpose, systemic analysis has been adopted by grouping the input parameters, which are being called as "strategies" listed in Table 3 below.

Table 3: Strategies for Analysing BPNN Performance

STRATEGY	INPUT PARMETERS	OUTPUT OBSERVED	REMARK
I	CR, IT, W_{OBS}	CO	Basic strategy is Strategy-I, which is followed by gradual addition and deletion of other parameters obtained from sensors signals.
II	CR, IT, W_{OBS}, PP		
III	CR, IT, W_{OBS}, θ_{peak}		
IV	CR, IT, W_{OBS}, PP, θ_{peak}		
V	CR, IT, W_{OBS}, PP, θ_{peak}, R.F.I		
VI	CR, IT, W_{OBS}, PP, θ_{peak}, Air pr., R.F.I		
VII	CR, IT, W_{OBS}, T_1, T_2, T_5, PP, θ_{peak}		

IV. Heuristic Optimization of BPNN and Its Parameters

Firstly, the architecture of each strategy is optimized by changing the number of neurons in the hidden layer, keeping Learning Rate (L.R) and Momentum Parameter (M.P) [6, 7] fixed respectively at 0.5 and 0.7 (the range being 0.1-20 and 0.7-5 for L.R and M.P respectively) to obtain a minimum mean squared error for the testing set of data or 25000 iterations, whichever occurs first and then the optimized architecture is further tested by varying the L.R and M.P to further minimise the error for the testing set. The optimized results are obtained by iterating the training and testing set with the program using back propagation algorithm. The following inputs are fed to the program:

Learning Rate (LR), Momentum Parameter (MP), No. of layers (3), Architecture (input neurons, hidden neurons, output neurons), Iterations (25000), Display interval (5), and Desired Mean Squared Error for testing data (MSE_{TS} = 0.001)

V. Result and Discussion

Best results compiled for CO emission are listed in Table 4.

Table 4: Best result for CO

Emission	Strategy	Architecture	L.R	M.P	Percent RMS Error		Iteration
					TRAIN	TEST	
CO	**IV**	**5-5-1**	**6**	**0.9**	**1.986**	**7.215**	**10850**

The learning curves and scatter diagrams of predicted and observed results for CO emission are depicted from Fig. 4 and 5.

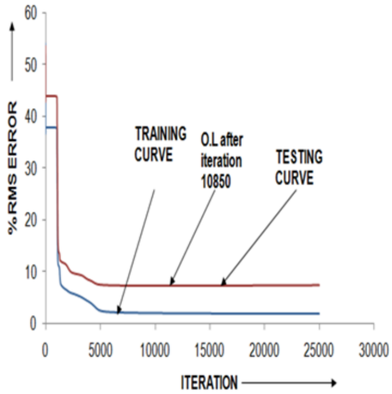

Fig.4 Learning curves for the heuristically best strategy IV of CO

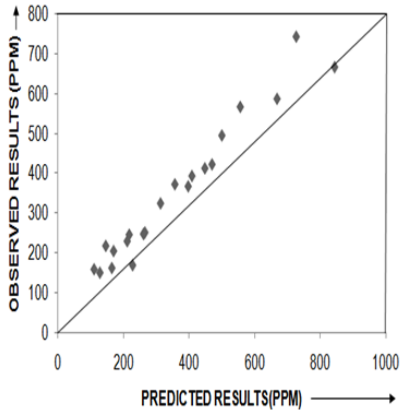

Fig.5 Observed V/S Predicted results for CO at iteration 10850 for strategy IV

VI. Inference

(i) The three basic controllable parameters compression ratio, observed load and injection timing as inputs are inadequate to predict CO emission within our limit of 25000 iterations. The minimum difference between observed and predicted results of training and testing set of data for 25000 iterations amounts to **78.876ppm and 85.9582ppm** respectively

(ii) The inclusion of **sensor signal feature** such as peak cylinder pressure (PP) and crank angle at the peak pressure (θ_{peak}) individually with the basic controllable parameters as stated in (i) gives a comparatively better result but the learning process continues beyond our limit. The minimum difference between observed and predicted results of training and testing set of data for 25000 iterations amounts to **85.094ppm and 86.634ppm** for strategy II and **63.0262ppm** and **82.1582ppm** for strategy III

(iii) The inclusion of both the sensor signal features along with the compression ratio, observed load and injection timing gives by far the best result as is evident from Fig.5 with a very fast rate of convergence with respect to the desired error for testing data as is evident from Fig. 4. The minimum difference between observed and predicted results of training and testing set of data for 25000 iterations amounts to **62.2985ppm and 81.515ppm** respectively

(iv) Strategy V and strategy VI gives bad result accompanied by **over-learning (O.L)**. The minimum difference between observed and predicted results of training and testing set of data for 25000 iterations amounts to **77.1418ppm and 92.886ppm** for strategy V and **77.3587ppm** and **94.5613ppm** for strategy VI

(v) But there is marked improvement in prediction results if we include the temperatures of water inlet and outlet to the engine and temperature of engine exhaust with the best strategy IV where minimum difference between observed and predicted results of training and testing set of data for 25000 iterations amounts to **72.1696ppm and 83.5105ppm** respectively

VII. Conclusion

With regard to the above analysis, strategy IV gives the predicted value of emissions close to their observed values. Strategy VII comes closer to IV. The cylinder peak pressure and crank angle at peak pressure (**θ_{peak}**) plays the most important role in emission prediction. It has been observed that the inclusion of indicted air pressure (**Air pr.**) and rate of fuel input into the cylinder (**R.F.I**) as inputs to the BPNN leads to poorer results in emission prediction.

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