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JAYPEE INSTITUTE OF INFORMATION TECHNOLOGY

Computational Intelligence (Semester VI)

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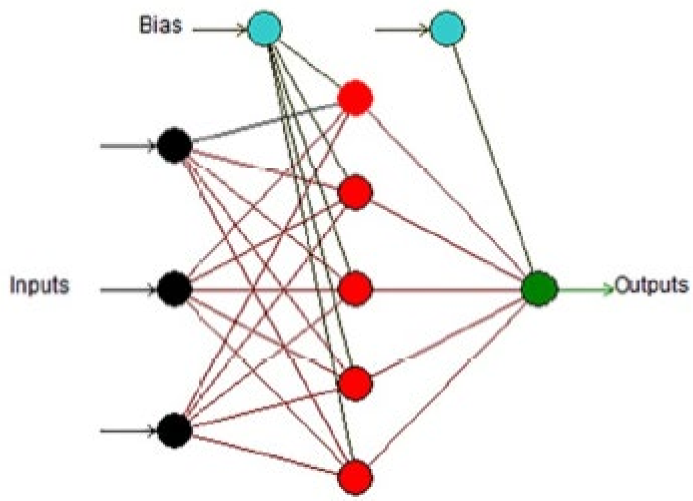
Report Notebook

INTEGRATED ANN-GA APPROACH FOR PREDICTIVE OPTIMIZATION OF GRINDING PARAMETERS WITH SURFACE ROUGHNESS AS THE RESPONSE

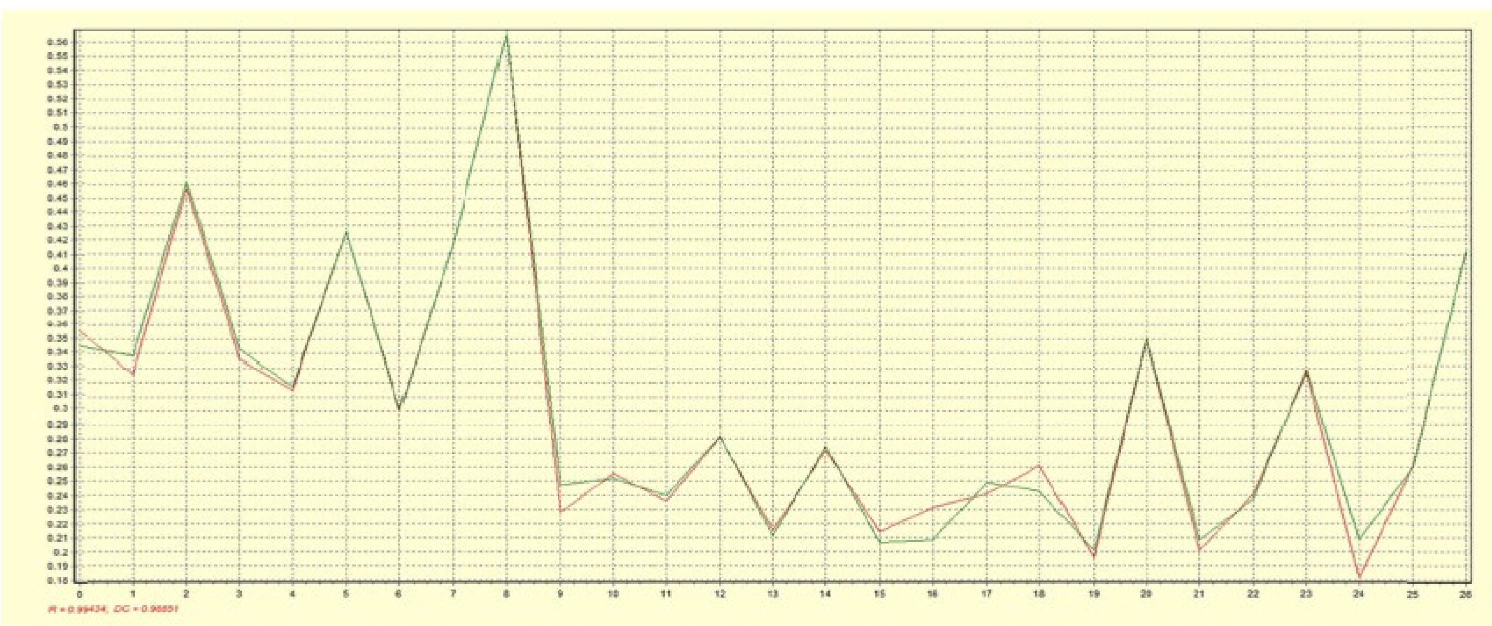
Authors: Vipin Gonan et al.

IN THIS WORK:

- Artificial neural networks are combined with genetic algorithm (GA) to develop a predictive and optimization model of grinding parameters.
- Three-layer normal feed forward ANN with structure 3-5-1 is used for the prediction of surface roughness.
- Although ANN itself yields value comparable to the experimental results, to ensure that the local minima is not mistaken for the global minima, the authors have incorporated GA with the ANN.
- Results demonstrate the feasibility of their model in predictive modelling and optimization of grinding parameters.



ANN architecture with 3-5-1 structure



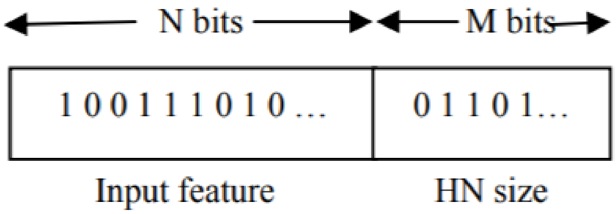
Correlation between experimental data and predicted output values

GENETIC ALGORITHM - ARTIFICIAL NEURAL NETWORK (GA-ANN) HYBRID INTELLIGENCE FOR CANCER DIAGNOSIS

Authors: Fadzil Ahmed et al.

IN THIS SECTION:

- GA has been used to simultaneously select significant features as input to ANN and automatically determine the optimal number of hidden node.
- The ANN training is done by Levenberg Marquardt (LM) algorithm.
- A new procedure in obtaining optimal ANN architecture is also described which is based on feature importance determined by Genetic Algorithm.
- Simulation results on cancer dataset proved that their proposed method has achieved the highest 97% average percentage of correct classification with the absent of 2nd and 5th feature.
- This paper has established a new procedure to obtain optimal ANN design. At first, simultaneous and automatic feature selection and determination of HN based on GA-ANN hybrid intelligence is used to find the feature importance. Based on the feature importance, a series of feature subset is manually created and the ANN is retrained using this subset. The approach which is based on a simple binary coded GA representation.



Binary Encoded GA representation

chromosome no	val MSE	ranking	fitness value
1	0.0258	1	5
2	0.0246	3	14
3	0.018	5	24
4	0.0257	2	10
5	0.0172	6	29
6	0.0229	4	19

An example of fitness value for each chromosome obtained from validation MSE

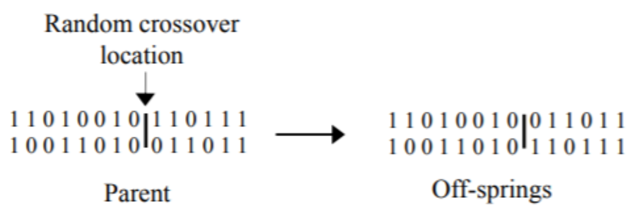
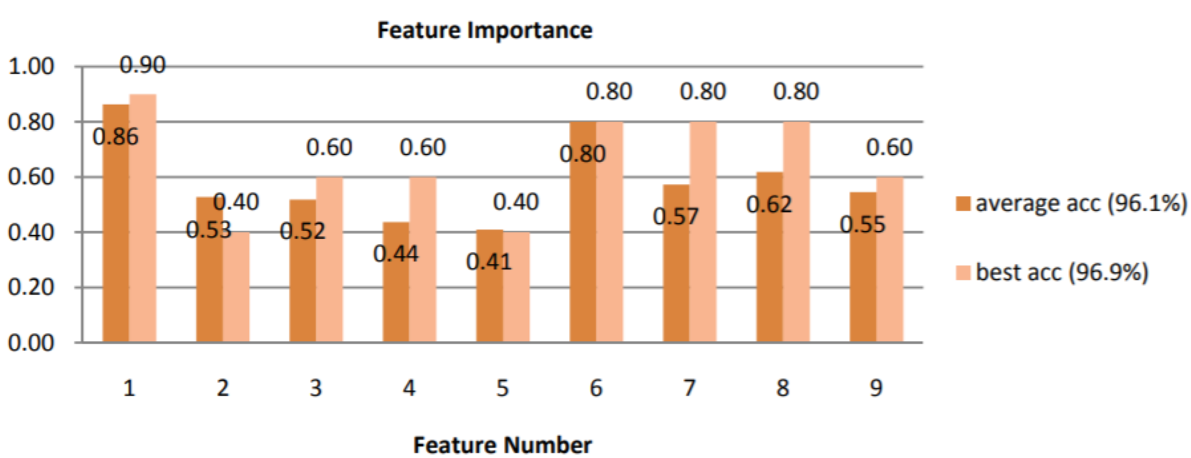


Figure 3. Single point crossover operation

Mutation Operation



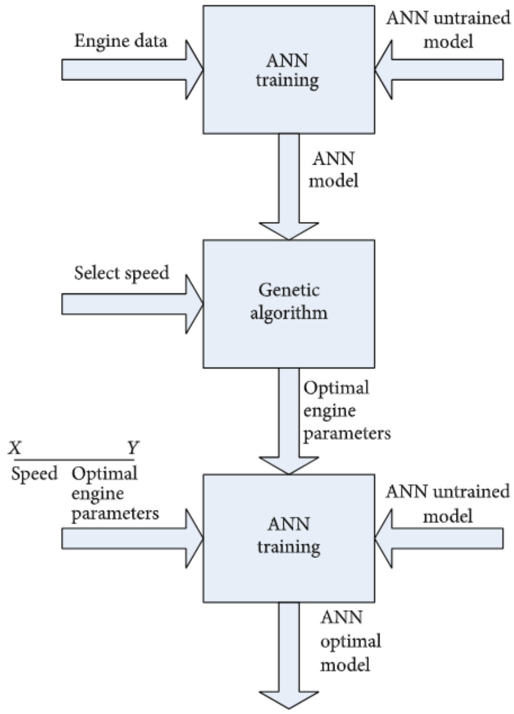
Comparison of feature importance between the best and average classification accuracy over 10 experiments

AN ANN-GA FRAMEWORK FOR OPTIMAL ENGINE MODELING

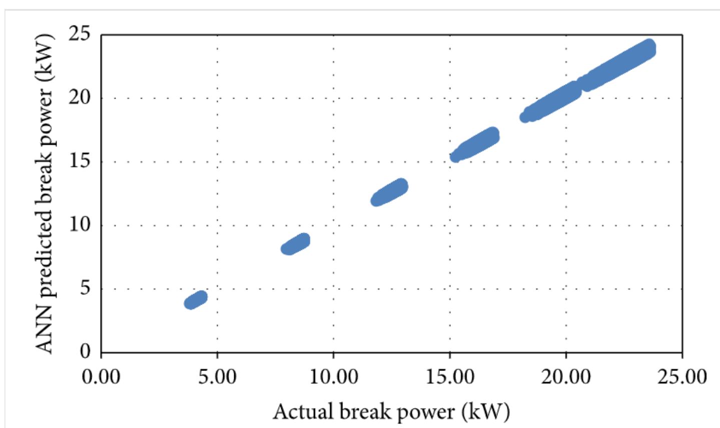
IN THIS SECTION:

- Artificial Neural Network (ANN) is used to model the effect of the VVT on the power and genetic algorithm (GA) as an optimization technique to find the optimal power setting.
- Based on the findings of this work, it was noticed that the VVT setting is more important at high speed.
- It was also noticed that optimal power can be obtained by changing the VVT settings as a function of speed.
- Also to reduce computational time in obtaining the optimal VVT setting, an ANN was successfully used to model the optimal setting as a function of speed.

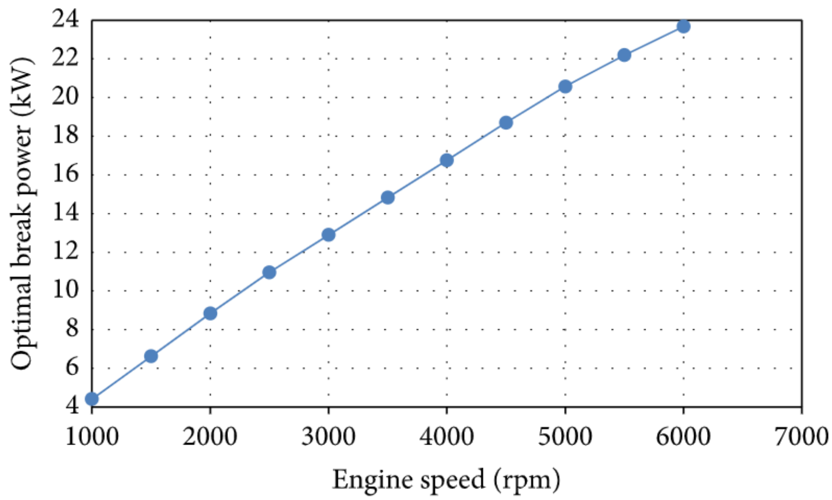
Authors:
Khaldoun K. Tahboub et al.



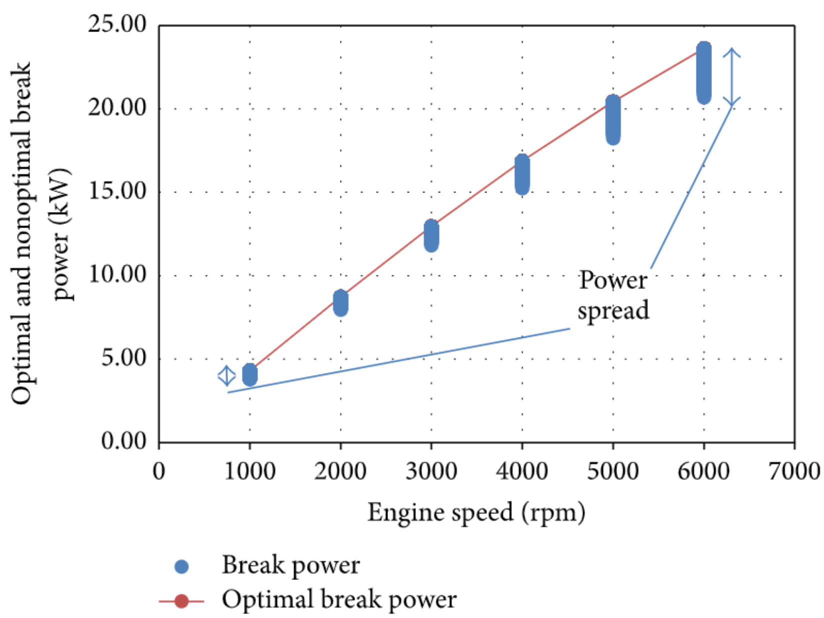
Proposed optimization methodology for SI engine timing settings.



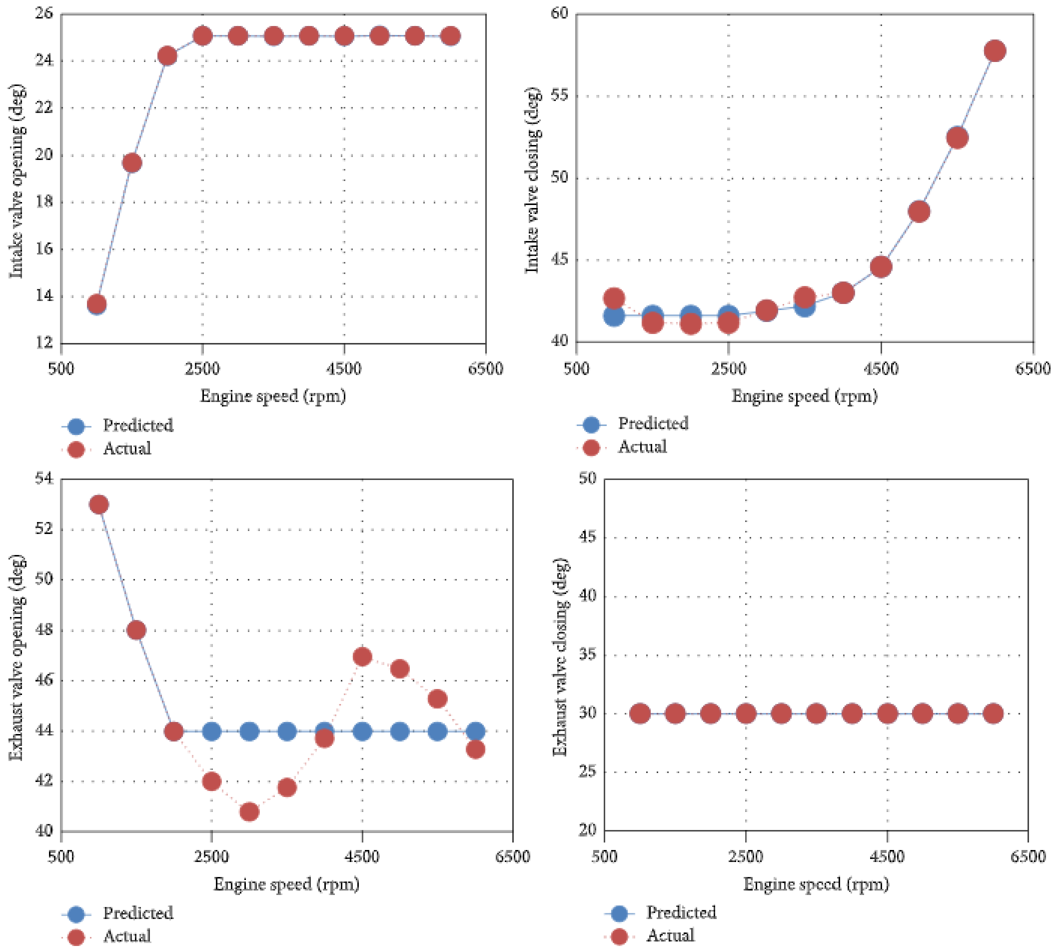
ANN prediction of engine power versus actual break power.



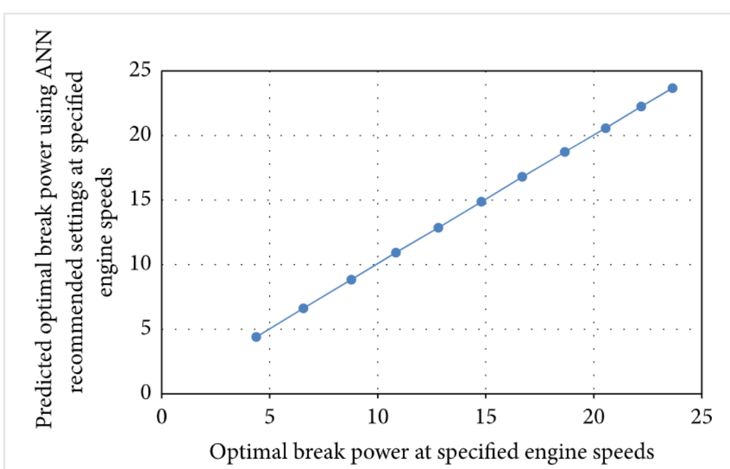
Optimal power in KW as predicted by NN-GA framework versus speed in RPM.



Power spread drawn for all the experimental VVT settings at different engine speeds in addition to optimal power (highest).



Optimal engine parameters as predicted by the GA-NN framework versus speed.



Validation of the final ANN; predicted optimal power versus actual optimal power.

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