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Original Article

The ensemble approach in comparison with the diverse feature selection techniques for estimating NPPs parameters using the different learning algorithms of the feed-forward neural network

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ABSTRACT

Several reasons such as *no free lunch* theorem indicate that there is not a universal Feature selection (FS) technique that outperforms other ones. Moreover, some approaches such as using synthetic dataset, in presence of large number of FS techniques, are very tedious and time consuming task. In this study to tackle the issue of dependency of estimation accuracy on the selected FS technique, a methodology based on the heterogeneous ensemble is proposed. The performance of the major learning algorithms of neural network (i.e. the FFNN-BR, the FFNN-LM) in combination with the diverse FS techniques (i.e. the NCA, the F-test, the Kendall's tau, the Pearson, the Spearman, and the Relief) and different combination techniques of the heterogeneous ensemble (i.e. the Min, the Median, the Arithmetic mean, and the Geometric mean) are considered. The target parameters/transients of Bushehr nuclear power plant (BNPP) are examined as the case study. The results show that the Min combination technique gives the more accurate estimation. Therefore, if the number of FS techniques is m and the number of learning algorithms is n, by the heterogeneous ensemble, the search space for acceptable estimation of the target parameters may be reduced from $n \times m$ to $n \times 1$. The proposed methodology gives a simple and practical approach for more reliable and more accurate estimation of the target parameters compared to the methods such as the use of synthetic dataset or trial and error methods.

1. Introduction

In recent years, many researchers have developed techniques for estimation/identification of future states of nuclear power plants (NPPs) using supervised learning algorithms to support operators' decision making process in the face of nuclear transients/accidents [1–7].

Supervised learning algorithms for estimating the target parameter constructs a mapping function between input patterns and the output patterns in the training process. To construct a mapping function which makes a balance between memorization and generalization some relevant features are needed [8]. The process of selection of relevant features is called feature selection (FS) technique.

Many different FS techniques for the target parameters in NPPs have so far been developed. Examples are: motor current signature analysis and classification of different failures [9], filter out irrelevant or redundant features based on classifiability index, features selection using the genetic algorithm (GA) and the particle swarm optimization (PSO) [10,11], and the ranking of features with minimum deviation from the target parameter (RFMD) technique for estimation of NPPs operating parameters [12].

The above mentioned techniques have their advantages and challenges. However, if the estimation accuracy is a measure for performance of a FS technique, this is dependent on the chosen learning algorithm. Several reasons such as *No free lunch* theorem [13] indicate that there is not a universal FS technique that outperforms other techniques. One of the solutions is to evaluate FS techniques using synthetic dataset, however, comparative study in presence of large number of FS techniques is almost an impossible task. Another approach is combination of multiple FS techniques. This combination is called *committee* or more recently *ensemble* [14]. Ensemble by combination of different techniques may help to obtain FS approach near the ideal approach which estimates the important parameters of NPPs more accurate [14–16].

This study seeks to introduce an ensemble for different FS techniques for estimating future states of important parameters of NPPs and to study its performance in comparison with the different FS

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techniques. This paper is structured as follow. In Section 2, a brief review of the different approaches of feature selection techniques and ensembles is given. In Section 3, the diverse FS techniques which are appropriate for parameters estimation is discussed. In Section 4, the Bayesian regularization (BR) and the Levenberg–Marquardt (LM) learning algorithms of the Feed-forward neural network (FFNN) are explained. The proposed methodology is illustrated in Section 5. The results of the target parameters/transients estimation using the given supervised learning algorithms are presented and are discussed in Section 6. Section 7 presents the conclusion.

2. A brief review of the different approaches of feature selection techniques and ensembles

The FS techniques in combination with the learning algorithms include the approaches of the filter, the wrapper, and the embedded. The output of the FS techniques can be a ranking of parameters or a subset of parameters.

The homogenous and the heterogeneous are the main ensemble approaches for the FS techniques. These approaches are presented in Fig. 1. In the homogenous ensemble, one type of FS technique with divided input to several partitions is used. In the heterogeneous ensemble, different types of FS techniques with the same training data are used [14].

Method of combination is used to integrate the results of the different FS techniques. If the outputs of FS techniques are subsets of the features, the methods including intersection, union, accuracy prediction [17], data complexity measures [18] are used. If the outputs of FS techniques are ordered ranking of the features, the methods including mean, median, arithmetic mean, geometric mean [19], etc. Are used.

The homogeneous ensemble is applied when the main goal is to reduce computational time [14]. In other words, the homogeneous ensemble distributes the data between a number of nodes to expedite the training process. In contrast, if there is an uncertainty about the selection of the specific FS technique and the main goal is to compare the efficiency of ensemble approach with diverse FS techniques, the heterogeneous ensemble is utilized.

3. The filter based feature selection techniques

The filter approach is independent of the learning algorithm and can therefore be suitable for studying the performance of the different FS techniques compared to the ensemble approach. A schematic view of the filter approach is presented in Fig. 2.

FS which is based on ordered ranking of parameters has the advantage that all features are ranked according to their importance for the target parameter. Taking into account the filter based FS techniques which are suitable for parameters estimation, the known techniques including: 1- the cross-correlation based techniques [20], 2- the Neighborhood Component Analysis (NCA) technique [21], 3- the F-test technique [22], and 4- the Relief technique are selected. This particular set of FS techniques ae considered because: 1- they are based on different metrics and thus give diversity in the final ensemble, and 2- they are widely used by researchers. *A detailed description of these techniques has been provided in the above mentioned references.*

4. The learning algorithms of the feed-forward neural network

The high performance learning algorithms of the FFNN including the BR and the LM are used [23]. A brief description of these algorithms is given in the following subsections.

4.1. The bayesian regularization learning algorithm

FFNN can suffer from overfitting (i.e. imbalance between

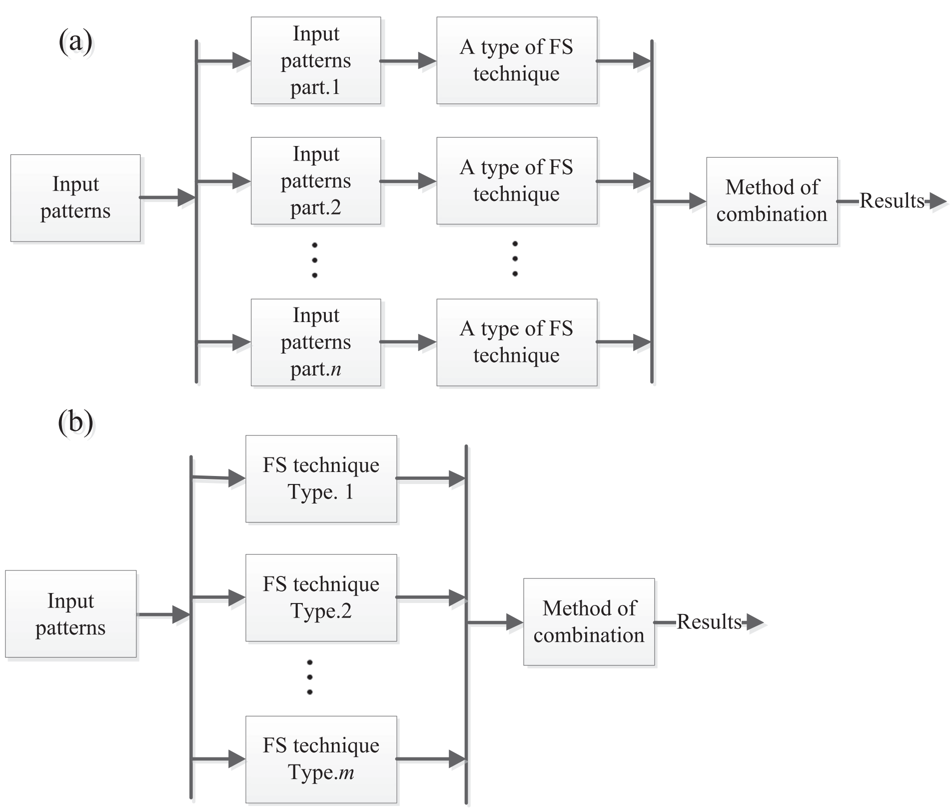

Fig. 1. A schematic view of (a) the homogenous (b) the heterogeneous ensemble approaches for selection of features.

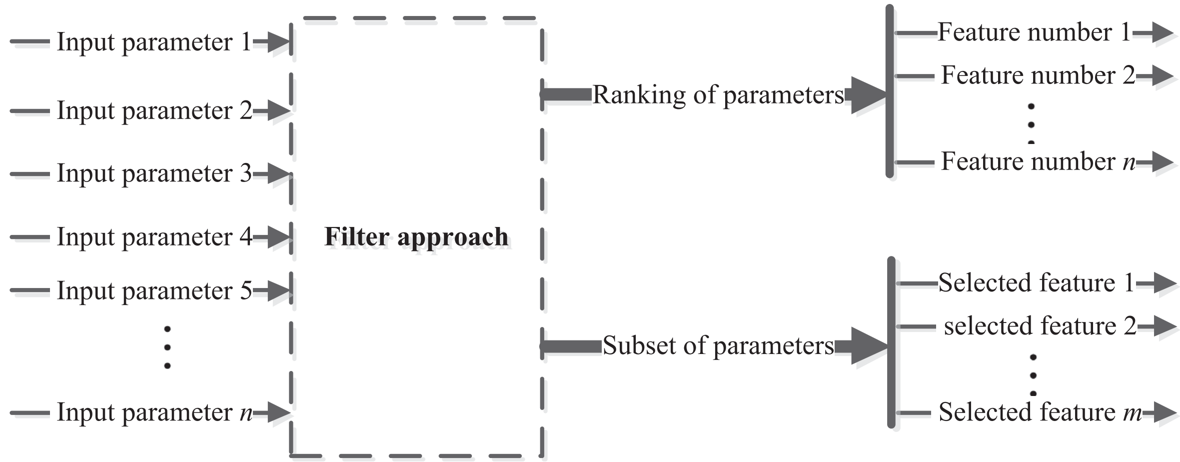

Fig. 2. A schematic view of the filter approach for selection of features.

memorization and generalization) [24]. In the BR learning algorithm, the Bayes' rule is used to update the weights of neural network.

And to overcome overfitting. The cost function (CF) of the BR learning algorithm is given by Eq. (1) [25]. Where, n and m are the number of input data and the number of output layer neurons, respectively, w_{kl} is weight between neurons k and l, and α and β are positive variables. Δ_{ij} is given by Eq. (2). T_{ij} and O_{ij} are network output and network target for input i and neuron j of output layer, respectively.

$$\begin{aligned} CF &= CF_{SD} + \beta \sum_{k=1}^{p} \sum_{l=1}^{q} w_{kl}^2 \\ CF_{SD} &= \alpha \sum_{i=1}^{n} \sum_{j=1}^{m} \Delta^2_{\Delta_{ij}} \end{aligned} \tag{1}$$

$$\Delta_{ij} = T_{ij} - O_{ij} \tag{2}$$

The parameters of α and β are given according to Eq. (3) and Eq. (4), respectively. Where, M stands for maximum posterior and γ is the number of parameters with more relative effect on decreasing the CF value.

$$\alpha = \frac{n - \gamma}{2 \sum_{i=1}^{n} \sum_{j=1}^{m} \Delta_{ij}^2 (w^M)} \tag{3}$$

$$\beta = \frac{\gamma}{2 \sum_{k=1}^{p} \sum_{l=1}^{q} w_{kl}^2 (w^M)} \tag{4}$$

The weights are distributed according to the Gaussian function and are given by Eq. (5). Where, P is probability function, $\boldsymbol{W}$ is weights vector, and $\boldsymbol{P}$ is input data vector.

$$P(\boldsymbol{W}|\boldsymbol{P},\ \alpha,\ \beta) = \frac{P(\boldsymbol{P}|\boldsymbol{W},\ \alpha)P(\boldsymbol{W}|\ \beta)}{\sum P(\boldsymbol{P}|\boldsymbol{W},\ \alpha)P(\boldsymbol{W}|\ \beta)\Delta \boldsymbol{W}} \tag{5}$$

4.2. The Levenberg–Marquardt learning algorithm

The weights of FFNN are updated conventionally using the steepest descent (SD) [26] algorithm which is given by Eq. (6), however, the convergence rate of the SD algorithm is small. The combination of the Gauss-Newton (GN) and the SD gives the stable and fast LM learning algorithm which is presented in Eq. (7). The GN is given by Eq. (8) where, J is Jacobian matrix, E is error matrix, and I is identity matrix.

$$\Delta w_{ij} = \frac{\partial CF_{SD}}{\partial w_{ij}} \tag{6}$$

$$\Delta w_{LM} = \Delta w_{GN} + \left(\frac{1}{\alpha} I\right)^{-1} JE \tag{7}$$

$$\Delta w_{GN} = \left(J^T J\right)^{-1} JE \tag{8}$$

5. The proposed methodology

There are two main steps in creating an ensemble for feature selection:

1 In the first step a set of different FS techniques is created to ensure the diversity,
2 In the second step the results of the FS techniques are combined.

There are several techniques that can be used to perform the second step. In this study different combination techniques are used.

The proposed methodology for investigating the performance of the heterogeneous ensemble in comparison with the different FS Techniques is given by the following steps:

1 Features ranking: The input parameters are ranked using a specific FS technique for estimating the target parameter/transient,
2 Repetition for a new FS technique: Step 1 is repeated for a new FS technique,
3 Heterogeneous ensemble for feature selection: The heterogeneous ensemble with a specific combination technique is used for the results of the different FS techniques,
4 Repetition for a new combination technique: Step 3 is repeated for a new combination technique,

5 Features selection: A number of features is selected,
6 Training of the learning algorithm: Seventy to eighty percent of the selected features data are used to train a specific supervised learning algorithm,
7 Test of the learning algorithm: Twenty to thirty percent of the selected features data are used to test the supervised learning algorithm,
8 Accuracy estimation: Average mean relative error (AMRE) and cumulative distribution function (CDF) which are given by Eq. (9) and Eq. (10), respectively, are used to give the estimation accuracy of the learning algorithm,
9 Repetition for a new learning algorithm: Steps 6 to 8 are repeated for a new learning algorithm,
10 Repetition for a new target parameter: Steps 1 to 9 are repeated for a new target parameter,
11 Comparison of the results: The results of the target parameters estimation are compared.

$$\mathrm{AMRE}=\frac{\sum_{i=1}^{R}\frac{\sum_{t=1}^{T}\frac{|\mathrm{Estimation}\ (t)-\mathrm{Reference}(t)|}{|\mathrm{Reference}(t)|}}{T}}{R} \tag{9}$$

$$CDF\left(E\right)=\sum_{i=\mathrm{minerror}}^{E}P(i)\left(=probability\ of\ prediction\ with\ error\ less\ than\ or\ equal\ \left(i\right)\right) \tag{10}$$

6. Case study: the target parameters/transients of Bushehr nuclear power plant

The target parameters/transients of Bushehr nuclear power plant (BNPP), a pressurized water reactor, are examined [27]. Uncontrolled withdrawal of control rods (UWCR) from the class of the anticipated operational occurrence (AOO) transients and sudden dysfunction of a reactor coolant pump (DRCP) from the class of the design basis accident (DBA) transients are selected as the case study.

6.1. The input and the target parameters

Two important parameters including fuel maximum temperature (FMT) and departure from nucleate boiling ratio (DNBR) are the target parameters. These type of parameters cannot be given by the NPPs sensors directly and therefore cross-correlation detection between these parameters and measurable parameters is necessary [26]. Accurate estimation of NPPs parameters can be used as a support system for the NPPs operators to perform more appropriate actions in critical situations. More than 4500 data points are extracted from the final safety analysis report (FSAR) of BNPP to give the input parameters and the target parameters/transients in Table 1.

6.2. The features ranking

The ranking of features for the target parameters/transients are presented in Table 2 and Table 3. The different FS technique give the different order of ranking.

6.3. The heterogeneous ensemble for the ranker features selection techniques

The heterogeneous ensemble for the ranker FS techniques using

Table 1
The input parameters and the target parameters/transients.

Target transients	Transient class	Input parameters	Target parameters
Uncontrolled withdrawal of control rods (UWCR)	AOO	Relative thermal power (RTP) (%)	FMT
		Relative heat flux (RHF) (%)	
		Relative neutron power (RNP) (%)	
		Pressure at core outlet (PCO) (MPa)	
		Coolant flowrate at core inlet (CFCI) (kg/s)	
		Coolant flowrate at core outlet (CFCO) (kg/s)	
		Pressurizer level (PL) (m)	
		Coolant temperature at core inlet (CTCI) (°C)	
		Coolant temperature at core outlet (CTCO) (°C)	
		Pressure in SG (PSG) (MPa)	
		Steam flowrate to turbine (SFT) (kg/s)	
Sudden dysfunction of a reactor coolant pump (DRCP)	DBA	Relative thermal power (%)	DNBR
		Pressure at core outlet (MPa)	
		Coolant temperature at core inlet (°C)	
		Coolant flow rate at the core inlet (kg/s)	
		Coolant temperature at core outlet (°C)	
		Coolant temperature at the steam-generator (SG) 2 outlet (CTSGO 2) (°C)	
		Coolant temperature at the SG 1,3,4 outlet (CTSGO 1,3,4) (°C)	
		Coolant temperature at the SG 2 inlet(CTSGI 2) (°C)	
		Coolant temperature at the SG 1,3,4 inlet (CTSGI 1,3,4) (°C)	
		Coolant flow rate in loop 2 (CFL2) (kg/s)	
		Coolant Flow rate in Loop 1 (CFL1) (kg/s)	
		Coolant flow rate in loop 3,4 (CFL 3,4) (kg/s)	
		Pressure in SG 2 (PSG 2) (MPa)	
		Pressure in SG 1, 3, 4 (PSG 1, 3, 4) (MPa)	
		Fuel enthalpy (FE) (J/g)	

Table 2
The ranking of features for FMT in UWCR transient using the FS techniques.

Features	NCA	F-test	Kendall's tau	Pearson	Spearman	Relief
	Ranking	Ranking	Ranking	Ranking	Ranking	Ranking
CTCI	1	9	9	8	10	1
PCO	2	8	10	9	9	5
SFT	3	5	1	7	1	11
CFCI	4	6	5	2	4	6
CFCO	5	7	6	3	5	7
RNP	6	3	4	6	6	10
PSG	7	10	11	11	11	2
RTP	8	4	3	5	3	9
RHF	9	2	2	1	2	4
CTCO	10	11	7	10	7	3
PL	11	1	8	4	8	8

different combination techniques which are Min, Median, Arithmetic mean, and Geometric mean [14] are presented in Table 4 and Table 5. These techniques are defined by the following statements:

1 Min: Assigning to each feature the minimum (best) position that it has achieved among all rankings.
2 Median: Assigning to each feature the median of all the positions that it has achieved among all rankings.
3 Arithmetic mean: Assigning to each feature the arithmetic mean of all the positions that it has achieved among all rankings.
4 Geometric mean: Assigning to each feature the geometric mean of all the positions that it has achieved among all rankings.

The Median, the Arithmetic mean, and the Geometric mean are given by Eq. (11), Eq. (12), and Eq. (13), respectively.

$$\text{median}(x)=\begin{cases}\dfrac{x_{\frac{n}{2}}+x_{\frac{n}{2}+1}}{2} & \text{for even number of FS techniques (i.e. } n) \\ x_{\left[\frac{n}{2}\right]+1} & \text{for odd number of FS techniques}\end{cases} \tag{11}$$

$$\text{arithmetic mean}(x)=\frac{1}{n}\sum_{i=1}^{n}x_i \tag{12}$$

$$\text{geometric mean}(x)=\left(\prod_{i=1}^{n}x_i\right)^{\frac{1}{n}} \tag{13}$$

Table 4
The ranking of features for FMT in UWCR transient using the different combinations of the heterogeneous ensemble.

Features	Min	Median	Arithmetic mean	Geometric mean
	Ranking	Ranking	Ranking	Ranking
CTCI	1	8	6	4
PCO	2	8	7	6
SFT	1	4	5	3
CFCI	2	4	4	4
CFCO	3	5	5	5
RNP	3	6	6	5
PSG	2	10	9	8
RTP	3	4	5	5
RHF	1	2	3	3
CTCO	3	8	8	7
PL	1	8	7	5

Table 5
The ranking of features for DNBR in DRCP transient using the different combinations of the heterogeneous ensemble.

Features	Min	Median	Arithmetic mean	Geometric mean
	Ranking	Ranking	Ranking	Ranking
CFCI	1	8	6	5
CFL2	1	2	4	2
CFL1	3	10	9	8
CFL34	4	10	10	9
FE	5	11	10	10
CTSGI2	6	10	10	9
PSG134	5	5	8	7
RTP	5	7	8	8
PSG2	6	6	8	8
CTSGO134	3	3	6	5
CTCI	2	2	4	3
CTSGI134	5	14	11	10
CTSGO2	1	1	4	3
PCO	1	14	10	7
CTCO	6	13	12	11

6.4. *The target parameters estimation*

To estimate the target parameters, two features with upper ranking for FMT in UWCR and three features with upper ranking for DNBR in DRCP are selected. Eighty/twenty percent of the selected features data are used for training/test of the learning algorithms. The estimation results of the FMT in the UWCR transient and the DNBR in the DRCP transient using the BR and the LM learning algorithms by the different FS techniques and by the different combinations of the heterogeneous ensemble are presented in Table 6 and Table 7, respectively. The results show that the estimation accuracy is dependent on the utilized FS technique. For estimation of

Table 3
The ranking of features for DNBR in DRCP transient using the FS techniques.

Features	NCA	F-test	Kendall's tau	Pearson	Spearman	Relief
	Ranking	Ranking	Ranking	Ranking	Ranking	Ranking
CFCI	1	6	8	8	8	7
CFL2	2	13	1	4	1	1
CFL1	3	8	9	11	10	13
CFL34	4	12	12	9	11	12
FE	5	11	11	12	12	11
CTSGI2	6	9	10	10	9	14
PSG134	7	15	5	5	5	9
RTP	8	5	7	7	7	15
PSG2	9	14	6	6	6	8
CTSGO134	10	4	4	3	4	10
CTCI	11	2	3	2	3	2
CTSGI134	12	7	14	15	14	5
CTSGO2	13	3	2	1	2	3
PCO	14	1	15	13	15	4
CTCO	15	10	13	14	13	6

Table 6
Average mean relative error (AMRE) and cumulative distribution function (CDF) for estimation of the FMT in UWCR transient (R = 100, CDF = 0.90).

The different FS techniques												
	NCA		F-test		Kendall's tau		Pearson		Spearman		Relief	
	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF
BR	0.09	0.11	0.14	0.16	0.32	0.38	0.61	0.64	0.32	0.38	0.21	0.26
LM	1.19	3.03	0.76	1.37	1.27	1.97	0.92	1.39	1.27	1.97	0.98	2.44

The different combination of the heterogeneous ensemble								
	Min		Median		Arithmetic mean		Geometric mean	
	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF
BRrowhead	0.05	0.06	0.27	0.31	0.61	0.64	0.24	0.27
LMrowhead	0.26	0.51	0.78	1.50	0.99	1.91	0.80	1.94

FMT parameter in UWCR transient, the NCA technique with FFNN-BR gives more accurate results than other FS techniques. On the other hand, the F-test technique with FFNN-LM is more accurate for estimation of FMT in UWCR. For estimation of DNBR parameter in DRCP transient, the F-test with the FFNN-BR and the Pearson with the FFNN-LM give more accurate estimation. Therefore, the results indicate that there is not a specific FS technique that outperforms other techniques. This is while the heterogeneous approach presents remarkable results. For estimation of FMT in UWCR transient and DNBR in DRCP transient, the Min combination technique gives the more accurate results than other combination techniques. In other words, with an appropriate selection of the combination technique, the challenge of dependency of estimation accuracy on the selected FS technique can be overcome.

The estimation of FMT in UWCR transient using the Min combination technique and the FFNN-BR neural network is given by Fig. 3. Fig. 4 presents the estimation of DNBR in DRCP transient using the Min technique and the FFNN-LM neural network. The superiority of the Min combination technique with the FFNN-BR compared to the most accurate FMT estimation which is given by the NCA technique and the FFNN-BR is presented in Fig. 5. CDF of DNBR estimation using the Min technique and FFNN-LM is illustrated in Fig. 6 and is compared to the most accurate DNBR estimation which is given by the F-test technique and the FFNN-BR in which the mean relative error (MRE) is given by Eq. (14).

$$\mathrm{MRE} = \frac{\sum_{t=1}^{T} \frac{|\text{Estimation result }(t) - \text{Reference}(t)|}{|\text{Reference}(t)|}}{T} \tag{14}$$

The proposed methodology leads to the following major advantages:

1 If the number of FS techniques is m and the number of learning algorithms is n, by the heterogeneous ensemble, the search space for acceptable estimation of the target parameters can be reduced from $n \times m$ to $n \times 1$.
2 The estimation results by an appropriate combination technique (e.g. the Min technique) can be more accurate than the results of the diverse FS techniques.
3 The heterogeneous ensemble gives a simple and practical approach for estimation of the target parameters compared to the use of synthetic dataset or trial and error methods.

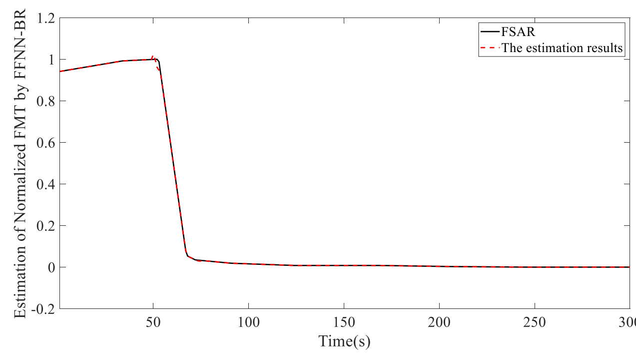

Fig. 3. The estimation of FMT in UWCR transient using FFNN-BR with Min combination technique.

It is important to mention, according to No free lunch theorem, there is not a universal FS technique that outperforms other ones and the Min technique is no exception to this theorem. Ensemble techniques only reduce the degree of dependence of parameters estimation results on FS techniques. But the reason why the Min technique gives better estimates than other ensemble techniques is

Table 7
AMRE and CDF for estimation of the DNBR in DRCP transient (R = 100, CDF = 0.90).

The different FS techniques												
	NCA		F-test		Kendall's tau		Pearson		Spearman		Relief	
	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF
BR	0.14	0.25	0.03	0.05	0.14	0.38	0.05	0.13	0.14	0.38	0.14	0.36
LM	0.19	0.37	0.04	0.07	0.12	0.27	0.04	0.06	0.12	0.27	0.11	0.27

The different combination of the heterogeneous ensemble								
	Min		Median		Arithmetic mean		Geometric mean	
	AMRE	CDF	AMRE	CDF	AMRE	CDF	AMRE	CDF
BR	0.02	0.06	0.15	0.43	0.08	0.23	0.13	0.38
LM	0.01	0.02	0.11	0.23	0.07	0.13	0.11	0.20

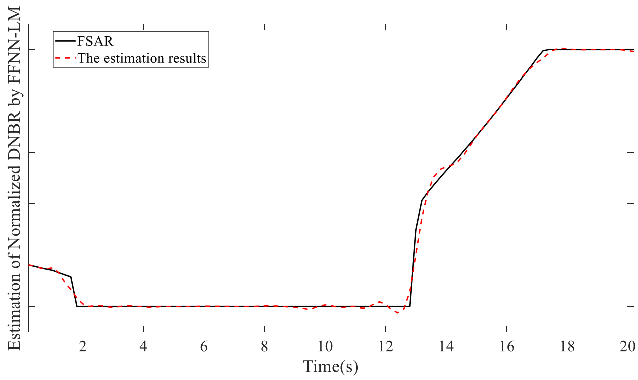

Fig. 4. The estimation of DNBR in DRCP transient using FFNN-LM with Min combination technique.

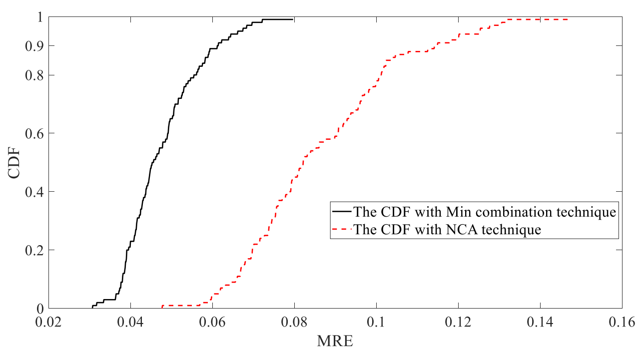

Fig. 5. The CDF of FMT estimation in UWCR transient with Min combination technique and NCA technique using FFNN-BR.

because of its conservative approach. This technique assigns the best position for feature that it has achieved among all rankings. In other words, the Min technique uses any FS technique with the feature that has the highest rank (i.e. the best output) in that technique to produce the final set of features. In contrast, other ensemble techniques used in this study apply an averaging method to produce the final features set, which to some extent overshadows the comparative advantages of the different FS techniques.

7. Conclusion

Several reasons such as *No free lunch* theorem indicate that there is not a universal FS technique that outperforms other FS techniques. On the other hand, some approaches such as using synthetic dataset, in presence of large number of FS techniques, are almost an impossible task.

In this study, to tackle the issue of dependency of estimation accuracy on the selected FS technique, a methodology based on the heterogeneous ensemble is proposed.

To examine the proposed methodology, the target parameters/transients of BNPP including FMT parameter in UWCR transient and DNBR parameter in DRCP transient are considered. The major learning algorithms of neural network (i.e. FFNN-BR and FFNN-LM) are utilized for estimation of the target parameters/transients. The diverse and known techniques including NCA, F-test, Kendall's tau, Pearson, Spearman, and Relief are used for features ranking. The different combination techniques of the heterogeneous ensemble including Min, Median, Arithmetic mean, and Geometric mean give the different order of ranking for features. The results show that, there is not a specific FS technique that outperforms other techniques. However, the Min combination technique gives the more accurate estimation. Therefore, if the number of FS techniques is m and the number of learning algorithms is n, by the heterogeneous ensemble, the search space for acceptable estimation of the target parameters may be reduced from $n \times m$ to $n \times 1$.

The proposed methodology gives a simple and practical approach for more reliable and more accurate estimation of the target parameters compared to the use of synthetic dataset or trial and error methods.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

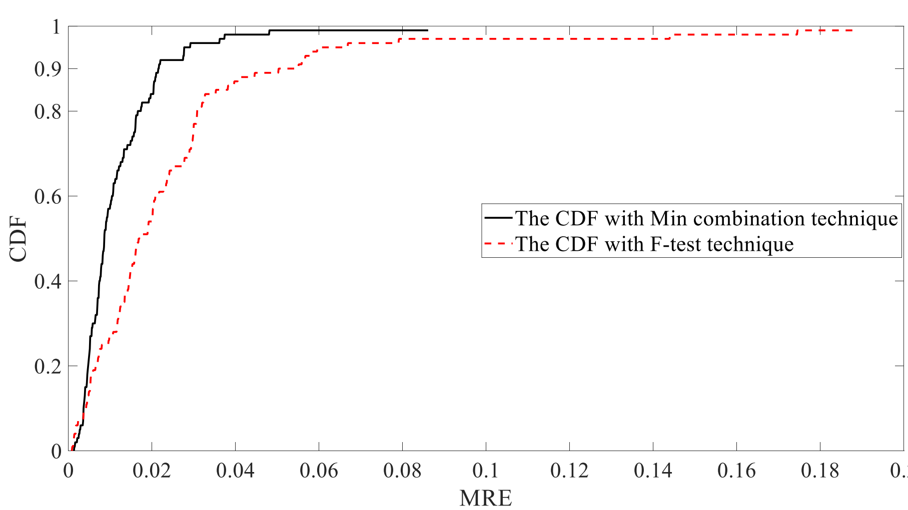

Fig. 6. The CDF of DNBR estimation in DRCP transient with Min combination technique using FFNN-LM and F-test technique using FFNN-BR.

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