General Regression Neural Networks for the Timely, Reliable and Efficient Monitoring, Detection, Localization, Identification of Detector Malfunctions as well as of Nuclear (Power) Plant Deviations from Steady-State Operation

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Abstract—**The analysis of nuclear (power) plant (N(P)P) neutron flux (NF) signals is imperative for ensuring safe and optimal[1] on-line N(P)P operation. Rather than the NF signals per se, it is the NF signal perturbations that are of interest, as the latter provide precise information concerning the instantaneous (relative) changes in N(P)P operation/status. In this piece of research, general regression artificial neural networks (GRNNs) are implemented for monitoring and concurrently identifying (detecting, classifying and localizing) both N(P)P deviations from steady-state operation and neutron detector (ND) malfunctions, in a timely, reliable and maximally efficient manner. The proposed approach accomplishes modularity and flexibility of operation by employing (a) raw NF signals as its source of information and (b) complementary NF signal encodings – derived from pertinent ND configurations – of the problem space. The use of GRNNs is found most satisfactory for the present monitoring/operation and malfunction detection/localization task, combining (i) low computational (time as well as space) complexity during GRNN training and testing, implemented by the straightforward optimization of the spread (σ) parameter and single-pass training/testing, with (ii) transparency of construction and (iii) accuracy and consistency in the identification of the cause(s) behind deviating-from-normal N(P)P behaviour, (iv) partial only GRNN retraining following modification of the training set. It is envisaged that appropriately combining the responses derived from different GRNNs shall further improve both the accuracy and the sensitivity of deviation/malfunction detection.**

Keywords—general regression artificial neural network (GRNN), polynomial (PA) approximation, semi-parametric spline (SPS), nuclear (power) plant (N(P)P), neutron detector (ND), neutron flux (NF), neutron noise, normal/deviating operation, instrumentation malfunctioning, cross-validation (CV)

[1] expressed in terms of minimal fuel use for maximal energy production

I. INTRODUCTION

Nuclear (power) plant (N(P)P) [1] construction is based on considerably detailed, complex models which relate modes of N(P)P operation to macroscopic cross-sections. Determining/predicting/monitoring N(P)P operation requires the formulation of the neutron flux (NF) perturbations/fluctuations [2] of NF signals, which is implemented – as a rule – via pertinent and minutely detailed models created by experts prior to (and as a guide for) N(P)P construction. Although such models accurately express the underlying physical phenomena and processes, their derivation is highly complex, as is their understanding and subsequent application.

It is, thus, advantageous to use expert opinion for building a simplified, yet sufficiently detailed, model of the N(P)P of interest based on a comprehensive set of data which relates the observed/captured NF perturbations to macroscopic cross-sections [2]. The resulting simulations constitute pertinent abstractions of the underlying processes, where the outputs can be directly related to the location and characteristics of the driving perturbation(s). It is customary to use the derived simulated signals [3] for defining and expressing the modes of operation of the N(P)P of interest as well as for investigating (detecting, identifying and rectifying) the N(P)P problems that may arise during operation; special emphasis is placed on N(P)P regime transitions and on situations where the in- and/or ex-core instrumentation is scarce.

[2] caused mainly by (i) two-phase (liquid/gas) coolant flow as well as (ii) perturbations of physical processes
[3] as well as those derived from the formulae/models created during N(P)P design preparation/formulation

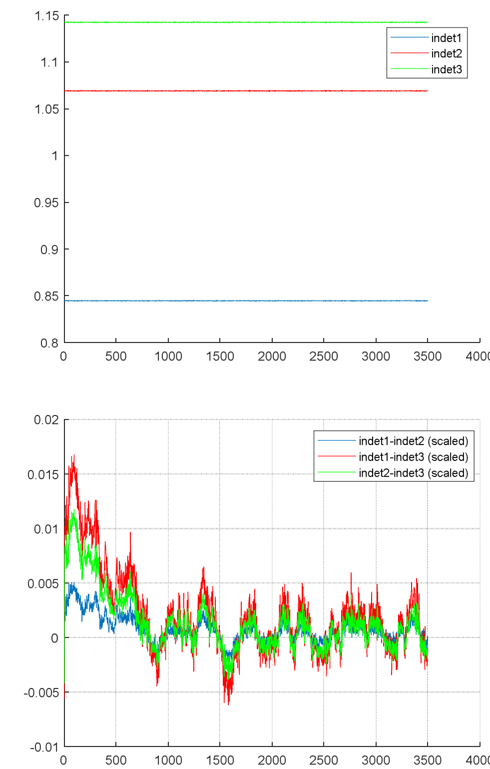
The focus of this research is upon non-parametrically (rather than analytically) inverting the reactor transfer function for recovering the processes that are responsible for the observed fluctuations, thus enabling (i) the detection of deviating-from-normal NF signals and (ii) the identification of the cause(s) behind such operation. By utilizing the minimum (a) number of neutron detector (ND) signals and (b) signal length, the proposed methodology is rendered (A) modular, (B) implementable in a maximally (time and space) computationally efficient manner and (C) capable of producing timely and – at the same time – reliable decisions on signal validity as well as on the identity/cause[4] of the observed deviations from expected operation.

This contribution is organized as follows: Section II introduces the general framework of N(P)P monitoring as well as of signal anomaly/ND malfunction detection; Section III implements signal verification and prediction via both parametric polynomial approximation (PA) [3], semi-parameric spline (SPS) [4] and non-parametric general regression artificial neural network (GRNN) [5] approaches on the datasets of [6-7] as well as on parts thereof systematically derived from 10-fold cross-validation (CV) [8], thereby establishing the validity and generalization properties of the three approximations on the problem at hand; Section IV critically presents and compares the prediction/verification results of the datasets, with Section V summarizing the results and putting forward future research aims concerning N(P)P monitoring and diagnosis.

II. N(P)P Monitoring – NDs, Neutron Noise Signals & Problem Formulation

A. *Neutron Noise Signals - N(P)P Signal/Detector-Related Problems*

Neutron noise signals constitute the prevalent source of information for performing N(P)P system analysis and identification as well as real-time characterization of the N(P)P operation mode and status. Further to the pure neutron noise part – which is inherent in the neutron noise signal per se and crucial for system verification and on-line monitoring purposes – these signals may also encompass signal drifts and/or more systematic oscillations, which result from such – common, yet crucial – factors [2] as (a) core barrel beam mode, (b) cylindrical component shell mode, (c) cylindrical component mode, as well as (d) fuel assembly beam mode[5], as well as other temporary and/or harder to define sources, thus effectuating – at times – a significant distortion/corruption of the neutron noise signal to be analyzed. It is important that the various source(s) of N(P)P signal corruption can be distinguished and characterized as:



(a) (b)

Fig. 1 The original INDET1, INDET2 and INDET3 signals (a), and the pairwise differences of the same signals following their (independent) scaling (b).

(i) a fluctuation or distortion of the neutron noise signal (random or more systematic)[6];
(ii) malfunctioning of the ND per se, e.g. ND bias, intermittencies, consequently hindering correct signal capture in varying ways and to different degrees.

The present aim is to accomplish swift and accurate monitoring, anomaly detection, localization as well as identification of diverging N(P)P operation while minimizing the computational complexity of signal processing and validation. To this end, the use of (i) the minimum number of ND signals collected for (ii) the shortest possible time-window, is implemented.

It is important to mention that, for longer time-windows and/or less stringent on-line operation requirements, moving-window wavelets and wavelet multiresolution analysis [9] can be applied to the signals as an alternative/complementary, dependable as well as robust, frequency-based signal analysis tool (e.g. [10]).

[4] herein confined to abnormal perturbations and/or malfunctioning neutron detector(s) (ND(s))
[5] which are also characteristic (unique) to the specific N(P)P
[6] yet excluding the noise that is inherent in the neutron noise signal per se, which is crucial for system identification and verification purposes

B. Number and Location of Required/Used NDs

For the purposes of efficiency and timeliness of response[7], rather than using all the available ND signals in concert, the concurrent utilization of 3-tuples of ND signals is proposed for verifying signal correctness as well as for boosting collective ND performance.

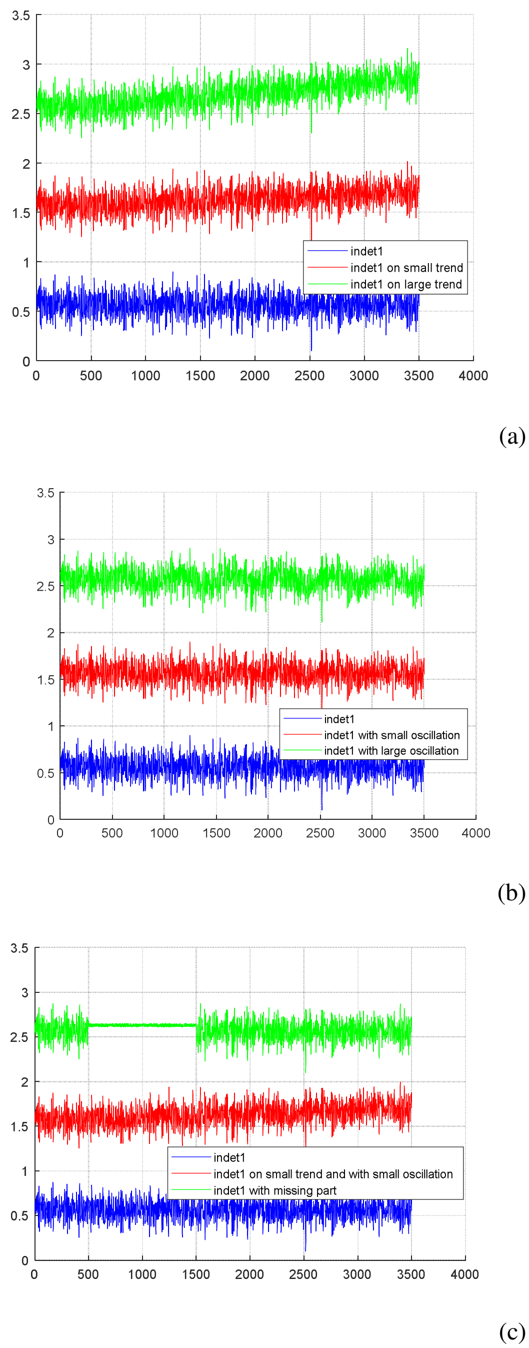


Fig. 2 Examples of drift (a), fluctuations (b) and drift/ fluctuation combinations of as well as intermittencies (c) applied to the normalized signal INDET1 (blue signal at the bottom of each illustration).

The rationale behind such a choice is that, although two NDs are not adequate for the task-at-hand[8], three NDs can be used as a means of competently as well as confidently deriving signal validity, implemented by two pairwise – and, only if desired/required, also a three-tuple – tests. Further to the modularization and transparency of the decision-making process, both the robustness and the swiftness of the final decision are maximized in cases of erroneous/unexpected signals and/or of failing NDs. The concurrent use of three-tuples of NDs further covers the far-from-infrequent situation of scarce in- and ex-core instrumentation, where strategically selected sets of three NDs are capable of reliably detecting and – furthermore – verifying the health-status of the NDs, as well as of, subsequently, analyzing the information encoded in the neutron noise signals.

Aiming at timeliness (on-line response) and efficiency of operation, the minimal signal length that guarantees confident signal verification is utilized. It is important that the collected signals from the selected NDs be highly correlated pairwise, so that – in case of signal corruption or component malfunction – the change (drop) in correlation between one or more pairs of signals can act as an early sign of decreasing agreement between these signals, which can be exploited directly for efficiently identifying the erroneous signal(s) and/or the malfunctioning ND(s). It is also possible to aggregate the decisions of different combinations of NDs (based, for instance, on signal correlation, ND location and distance) for reaching a consensus-driven decision which

In det 1	In det 2	In de t3	Indet1→ Indet2	Indet3→ Indet2	Indet1 & Indet3 → Indet2
√	√	√	√ (× if Det2×)	√ (× if Det2×)	√ (× if Det2×)
√	√	×	√ (× if Det2×)	×	×
√	×	√	×	×	×
×	√	√	×	√ (× if Det2×)	×
√	×	×	×	×	×
×	√	×	×	×	×
×	×	√	×	×	×
×	×	×	×	×	×

TABLE I. RELATIONSHIP BETWEEN CORRELATED ND SIGNALS INDET1, INDET2 AND INDET3 DEPENDING ON (A) SIGNAL CORRECTNESS AS WELL AS (B) CORRECT OPERATION OF THE NDS PER SE (DET1, DET2, DET3) ; ERRONEOUS SIGNALS AS WELL AS MALFUNCTIONING DETECTORS ARE MARKED BY ×.

[7] the more detectors used, the more substantiated the decision, yet the higher the computational time/space complexity of the required analysis

[8] since – in case of disagreement between pairs of ND signals – it is not possible to establish which ND is misbehaving and/or receiving abnormal information

takes into account each ND-derived decision, while – at the same time – also exploiting the confidence in, as well as the complementarity of, the individual decisions.

C. Modes of N(P)P Operation and Deviations from Normal Operation – Problem Formulation

In the following description and demonstration, three-tuples of signals derived from SIMULATE-3K [6], named here INDET1 and/or INDET3 (collected by detectors D1 and D3, respectively) are used for demonstrating the prediction of signals INDET2 (collected by detector D2). A set of three such signals is shown in Fig. 1(a), with Fig. 1(b) further demonstrating the pairwise relationships between these signals, derived by independently normalizing each signal in the [0.1 0.9] interval and subtracting one signal from the other; both the high-frequency fluctuations, which are largely due to the inherent – and most important in signal analysis and identification – noise in the neutron signals, and other kinds of fluctuations can be observed at different time-stamps and scales (frequencies). Despite their differences (Fig. 1(b)), these signals are highly correlated (with their pair-wise correlation coefficients ranging in [0.85 0.99]), thus rendering the ensuing investigation a proof-of-concept test.

The three approximation/prediction methodologies (PAs, SPSs and GRNNs) are implemented in identical fashion for monitoring and concurrently identifying (detecting, classifying and localizing) both N(P)P deviations from steady-state operation and neutron detector (ND) malfunctions in a timely, reliable and maximally efficient manner and, subsequently compared. The procedure is described next for the {INDET1,INDET2} pair of input-output neutron-noise signals, yet is directly transferable to the other two (one pair and one triplet of) signals employed for training each GRNN; during testing, INDET1/3/1&3(t') is/are used for predicting INDET2(t'), t'≠t. The PA, SPS and GRNN methodologies are implemented, independently each, yet under identical conditions of data normalization and partitioning.

The following tests involve the original signals, as well as their corrupted versions, which take on the form of:

- Drifts, implemented by adding linear trends to the original signals; different amplitudes of the slope are used for investigating the capability of, as well as the "limit" on, successfully retrieving the original (trend-free) signals. A small and a large trend (TS an TL, respectively), from the trends used in the present tests, are shown in Fig. 2(a).
- Fluctuations, simulated by adding sinusoidals to the original signals; as for the drift, different amplitudes and frequencies of the sinusoidals are tested, with a small and a large oscillation (OS an OL, respectively) of the same frequency appearing in Fig. 2(b).
- Combinations of drifts and oscillations (OT, Fig. 2(c)).
- Intermittencies (MR), where parts of the original signals are missing; simulating the real situation, these parts are substituted by the (local) mean value of the signal, overlaid with white noise of different amplitudes (Fig. 2(c)).

The absolute minimal signal length is used for signal verification, namely the {INDET1(t), INDET2(t)}, {INDET3(t), INDET2(t)} and {[INDET1(t), INDET3(t)], INDET2(t)} input-output pairs of signals captured at times t are employed for setting up the proposed approximation/prediction methodologies[9]. During testing, signals INDET1(t'), INDET3(t') or [INDET1(t'), INDET3(t')], captured at time t'(≠t), are used for predicting INDET2(t'). It is important that, in case of malfunction, the change (drop) in correlation between one or more pairs of

TABLE II. PA PEFORMANCE: DEVIATION BETWEEN ACTUAL AND PA-PREDICTED ND SIGNAL INDET2 FROM ND SIGNALS INDET1, INDET3 AND INDET&INDET3 DEPENDING ON (A) SIGNAL CORRECTNESS AS WELL AS (B) MALFUNCTIONING NDS PER SE (DET1, DET2, DET3); ENTIRE DATASET RESULTS (A-B).

PA input(s)	Indet1 to Indet2 vs Indet2	Indet3 to Indet2 vs Indet2	Indet1 and Indet3 to Indet2 vs Indet2
normal	2.4788e-16	2.1867e-16	5.0218e-17
TS	0.0643	0.0644	0.0447
TL	0.1287	0.1287	0.0894
OS	7.1806e-08	7.1806e-08	4.9883e-08
OL	1.7951e-07	1.7951e-07	1.2471e-07
OT	0.0644	0.0644	0.0447
MR	0.0156	0.0156	0.0111

(a)

PA input(s	Indet1 to Indet2 vs Indet2	Indet3 to Indet2 vs Indet2	Indet1 and Indet3 to Indet2 vs Indet2
normal	2.4788e-16	2.1867e-16	5.0218e-15
TS	3.3200e-04	2.3403e-05	0.0447 (Det1×) 0.0196 (Det3×) 0.0447(Det1,3×)
TL	6.6402e-04	4.6807e-05	0.0894 0.0393 0.1287
OS	3.7048e-11	2.6117e-12	4.9883e-08 2.1917e-08 7.1800e-08
OL	9.2620e-11	6.5290e-12	1.2471e-07 5.4793e-08 1.7950e-07
OT	3.3201e-05	2.3403e-06	0.0447 0.0196 0.0643
MR	2.7793e-04	1.5908e-04	0.0111 0.0045 0.0156

(b)

[9] this is rendered possible by the high correlation between the signal pairs; although longer records may well be needed for signals characterized by lower cross-correlation coefficients, record length should still be kept minimum so as to ensure low computational and time complexity of operation.

signals can (i) act as an early sign of decreasing agreement between them and (ii) be further exploited for identifying the erroneous signal(s) and/or the malfunctioning ND(s)[10]. It is also possible to aggregate the decisions of different combinations of NDs (based, for instance, on signal correlation, ND location and distance) for reaching a consensus-driven decision that takes into account each ND-derived decision while further exploiting the confidence in, as well as the complementarity of, the individual decisions.

Table I shows a simplified scheme of the effect that erroneous (marked as ×) signals Indet1, Indet2 and Indet3 and/or (ii) malfunctioning (also marked as ×) detectors Det1, Det2 and Det3 have on establishing (i) signal validity and (ii) ND (mal)functioning.

III. ND Signal Preparation for Verification/Monitoring/Prediction – Implemented Methodologies

A. *Problems Tackled – Inherent Data Errors, ND Malfunctions*

The three approaches use sets of identical – in terms of time of collection – input and output signals and are tested on identical parts of the dataset according to the use-all and 10-fold CV and, subsequently, compared.

Three distinct cases are investigated, namely (1) both input signals being correct and the ND(s) behaving normally; (2) the input signals being correct, yet – due to ND malfunction(s) – some, or all, of them being recorded erroneously; (3) (some, or all of) the signals per se being erroneous and the NDs operating normally. Furthermore, for the prediction of the INDET2 signal in the case where both the INDET1 and INDET3 signals are used, all the combinations of correct vs corrupted input signals and detectors operating as expected or malfunctioning (i.e. erroneously recording the signals) are examined. In the following, case (1) is reported and thoroughly analyzed. The results of case (2) are also reported but not further analyzed, as the effects of malfunctioning ND(s) cannot be sufficiently defined or confirmed by expert consultation; this is due to that fact that the effects depend on the ND per se, as well as on the kind and severity of malfunction, whereby expert judgment is necessary for confidently interpreting the recordings. In any case, it is assumed in the following that a distorted signal takes one the forms of the corrupted versions described in Section II.C.

[10] it is also possible/of interest, and a topic of future research, to adjust the length of the time-window depending on the current cross-correlation value between the pairs of INDET1, INDET2 and INDET3 signals

B. *Prediction Methodologies*

Three prediction/function approximation methodologies, which cover the entire parametric through to non-parametric spectrum, are used, namely PA, SPS's and non-parametric GRNN's.

While the parametric PA analytically determines the optimal polynomial coefficients such that the input variables approximate the output variable(s) by minimizing the distance (absolute or squared differences) between actual and predicted outputs, SPS's employ a set of predefined forms which are, subsequently, appropriately combined in a piece-wise manner (i.e. locally over the independent variable of the problem space) so as to optimally approximate the output variable(s) from the input variables.

The non-parametrically trained and operating GRNN, on the other hand, constitutes a two-layer artificial neural network architecture of straightforward as well as transparent construction, which makes use of a single parameter (σ, the spread). The GRNN implements (i) direct correspondence between its layers and problem elements/ characteristics, (ii) logic-based connectivity and automatic connectivity-based weight assignment, and (iii) single-epoch training for the creation of (iv) a non-parametric free-form, purely data-derived and σ-tuned optimal hypersurface that forms the separating hyperplane between pattern classes[11]. A single presentation of the training patterns is sufficient for setting the optimal form of a non-parametric curve such that correct outputs are returned to known inputs, as well as to novel inputs derived from the same pattern space. Due to the distance (σ-) dependent interaction between nodes for the formation of the GRNN output, the GRNN decisions are robust to noise.

The nodes of the two GRNN layers represent:

i. the input features (problem characteristics/ dimensions), with each feature being encoded in a single node of the lower layer of the GRNN;
ii. the training patterns, with each pattern encoded in a single node of the upper layer of the GRNN;
iii. the connections between nodes, which are only possible between nodes of different layers and, furthermore, limited between pairs of nodes (one node from each layer) which are related in a positive or negative manner, namely by whether the appearance of the input feature represented by the connected node of the lower layer is promoted or

[11] the value of σ determines the range of influence of each training pattern, and consequently the shape of the GRNN approximating hyperspace in terms of desired continuity of the separating hyperplanes; the smaller (vs larger) the value of σ, the more localized yet significant the influence of each training pattern on the separating hypersurface and, thus, the more detailed, specific/faithful to local detail (vs general) the interpolation between neighbouring training patterns

suppressed/opposed, respectively, in the training pattern represented by the connected node of the upper layer;

TABLE III. SPS PEFORMANCE: DEVIATION BETWEEN ACTUAL AND SPS-PREDICTED ND SIGNAL INDET2 FROM ND SIGNALS INDET1, INDET3 AND INDET1&INDET3 DEPENDING ON (A) SIGNAL CORRECTNESS AS WELL AS (B) MALFUNCTIONING NDS PER SE (DET1, DET2, DET3);); ENTIRE DATASET RESULTS (A-B).

SPS input(s)	Indet1 to Indet2 vs Indet2	Indet3 to Indet2 vs Indet2	Indet1 and Indet3 to Indet2 vs Indet2
normal	1.3256e-16	1.0652e-16	3.3348e-17
TS	0.0538	0.0517	0.0489
TL	0.1108	0.1200	0.1087
OS	3.6290e-09	3.6302e-09	9.9736e-10
OL	0.9532e-07	0.9532e-07	0.6580e-08
OT	0.0604	0.0611	0.0406
MR	0.0153	0.0154	0.0103

(a)

SPS input(s)	Indet1 to Indet2 vs Indet2	Indet3 to Indet2 vs Indet2	Indet1 and Indet3 to Indet2 vs Indet2
normal	1.3256e-15	1.0652e-15	3.3348e-15
TS	8.3092e-04	8.2499e-04	0.0506 0.0467 0.0506
TL	7.8407e-05	5.6649e-06	0.1278 0.0709 0.1684
OS	3.4520e-11	5.71383e-12	8.8106e-07 7.3301e-08 9.0054e-07
OL	8.2620e-11	6.5290e-12	1.9738e-07 6.7390e-08 2.3261e-07
OT	3.9201e-05	2.3403e-05	0.0168 0.0150 0.0190
MR	1.4322e-04	5.6301e-04	0.0232 0.0059 0.0288

(b)

iv. the connection weights, which are determined independently for each node of the upper layer; the magnitude of each non-zero connection emanating from a given node of the upper layer is the same towards all the connected nodes of the lower layer, determined as the inverse of the total number of non-zero connections that the node of the upper layer has with the nodes of the lower layer[12], with the +/-sign of the connection depending on whether the pair of connected (upper and lower-layer) nodes expresses a positive (reciprocal, reinforcing) or negative (opposing) relationship, respectively.

It is important that, in case of changes in the problem set-up and/or characteristics/data, which are expressed as pattern additions to/deletions from the dataset:

[12] i.e. the weights of all the connections emanating from a given node of the upper layer have the same absolute value

- a new node of the upper layer can added for each novel pattern, with the weights set in the same manner as for the original training patterns;

TABLE IV. GRNN PEFORMANCE: DEVIATION BETWEEN ACTUAL AND GRNN-PREDICTED ND SIGNAL INDET2 FROM ND SIGNALS INDET1, INDET3 AND INDET1&INDET3 DEPENDING ON (A) SIGNAL CORRECTNESS AS WELL AS (B) MALFUNCTIONING NDS PER SE (DET1, DET2, DET3);); 10FCV RESULTS (A-B).

GRNN input(s)	Indet1 to Indet2 vs Indet2	Indet3 to Indet2 vs Indet2	Indet1 and Indet3 to Indet2 vs Indet2
normal	3.6792e-02	3.6793e-02	5.9950-03
TS	0.0055	0.0057	0.0049
TL	0.0709	0.0073	0.0055
OS	5.6290e-10	5.8592e-10	3.7951e-11
OL	0.9532e-07	0.1263e-07	0.e-08
OT	0.0064	0.0067	0.0059
MR	0.0097	0.0076	0.0054

(a)

GRNN input(s)	Indet1 to Indet2 vs Indet2	Indet3 to Indet2 vs Indet2	Indet1 and Indet3 to Indet2 vs Indet2
normal	3.6792e-02	3.6793e-02	5.9950-03
TS	8.9425e-04	8.2494e-04	0.3179 0.0155 0.0376
TL	8.4722e-05	8.1506e-06	0.3378 0.2309 0.1195
OS	1.4520e-10	3.7383e-11	4.38523-06 7.6053e-07 7.1800e-07
OL	9.2620e-11	7.5295e-11	2.2471e-07 1.4793e-08 3.5824e-07
OT	7.3201e-05	5.7205e-06	0.1238 0.1160 0.1903
MR	8.9463e-03	6.9962e-03	0.0278 0.0089 0.0315

(b)

- GRNN nodes of the upper layer corresponding to training patterns which are no longer valid/needed can be directly deleted, together with the connections (and, thus, also the weights) emanating from these nodes;

where, in both cases, the approximating hyperplane is automatically adjusted.

For more information on GRNN training, testing and characteristics, the interested reader is referred to [5].

IV. N(P)P MONITORING – VERIFICATION/MONITORING/PREDICTION – IMPLEMENTED METHODOLOGIES

The following tests make use of (I) normal signals as well as of (II) signals which have been corrupted in the manner described in Section II.B, representing signal perturbations per se (shown in Tables II-IV(a)) as well as the GRNN nodes of the upper layer corresponding to training patterns which are no longer valid/needed can be directly deleted, together with the connections (and, thus, also the weights) emanating from these nodes;

where, in both cases, the approximating hyperplane is automatically adjusted.

For more information on GRNN training, testing and characteristics, the interested reader is referred to [5].

V. N(P)P Monitoring – Verification/Monitoring/Prediction – Implemented Methodologies

The following tests make use of (I) normal signals as well as of (II) signals which have been corrupted in the manner described in Section II.B, representing signal perturbations per se (shown in Tables II-IV(a)) as well as signal distortions caused by erroneous capture due to ND malfunctioning (shown in Tables II-IV(b)) for PA, SOS and GRNNs, respectively. In order to standardize GRNN operation, as well as guarantee its operation on novel data, rather than setting the optimal value of the spread (σ) parameter independently for each GRNN, all tests and cross-validation schemes have been performed using the value of $\sigma=0.05$. Such a choice represents minimal interpolation (confined to clearly confined "neighborhoods" of very similar patterns) and has been implemented for this problem in order to establish the focused – yet otherwise moderate and graded – interaction of training patterns for shaping the GRNN response. Small σ values overall, and the specific value of 0.05, in particular, has been found to consistently provide valid (though not always optimal) prediction results as well as to agree with the findings of Table I.

Table II exposes the accuracy of PA in predicting the INDET2 signal in a time-step-wise manner. The first line of Table II(A) provides the baseline of normal operation, thus highlighting the increased sensitivity of PA to the presence of trends (larger deviations from normal are observed for TL, TS and OT), with the MR situation not significantly affecting signal predictions. Oscillations, at least of the scale tested here, are significantly different to normal operation, but less degrading than either trends or missing signals, implying a certain robustness to such periodic-(shaped) signals. Table II(B) further confirms these findings, which imply that periodically malfunctioning NDs are less sensitive than those demonstrating signal drift, i.e. more liable to late detection of a fluctuating (rather than to a gradual) deterioration in their detection ability.

SPS operation has been found clearly superior to that of PA, demonstrating the advantages of the more degrees of freedom allowed by the specific piece-wise constructed methodology over PA. Furthermore, the GRNN approach has been found clearly superior to both PA and SPS approaches, by demonstrating

- perfect recall of the entire dataset, not only for the selected (0.05) but, for most values of the σ parameter when the entire dataset is used for training, as well as
- a level of prediction accuracy during testing that is at least comparable (and, in most cases, superior) to the level of approximation accuracy accomplished by the other methodologies (PA and SPS) when using the entire dataset for training/parameter setting.

VI. Conclusions

The on-line analysis of neutron flux (NF) signals – which are collected at nuclear (power) plants N(P)Ps for purposes such as monitoring, analysis, regime identification, transient as well as anomaly detection and isolation – is required for the safe as well as efficient operation of any N(P)P. NF perturbations are crucial, and have been used since the installation of the earlier N(P)Ps, for providing precise information concerning the instantaneous (relative) changes in N(P)P operation/status, and are customarily used for monitoring and, concurrently, identifying (detecting, classifying and localizing) (i) N(P)P deviations from steady-state operation and (ii) neutron detector (ND) malfunctions.

In this piece of research, a range of parametric, semi-parametric and non-parametric methodologies has been put forward and implemented for detecting and localizing deviations from steady-state (or otherwise scheduled) operation, as well as for identifying ND malfunctions. Aiming at robustness, modularity as well as low computational complexity, rather than using all the available ND signals in concert, it is proposed here to use 3-tuples of ND signals, thus simplifying the decision-making process as well as increasing the robustness of the final decision by collecting the decisions of 3-tuples of NDs and subsequently aggregating them for reaching a consensus-driven decision that takes into account each decision as well as the complementarity of the individual decisions.

The proposed approach accomplishes modularity and flexibility of operation by employing (a) raw NF signals as its source of information and (b) complementary NF signal encodings – derived from pertinent ND configurations – of the problem space. The use of GRNNs has been found most satisfactory for the present monitoring/operation and malfunction detection/localization task, combining

(i) low computational (time as well as space) complexity during GRNN training and testing, which is implemented by single-pass training/testing and the straightforward optimization of the (spread, σ) parameter, with
(ii) simplicity and transparency of construction and

(iii) superior accuracy in the identification of the cause(s) behind deviations from normal/scheduled N(P)P operation.

The non-parametric nature of the proposed GRNN allows the development of a tailor-made data-driven (rather than a more rigid system based on a specific N(P)P type of or, even, unit of a given) monitoring system, which can – furthermore – be directly adapted and, subsequently, applied to a large variety of data/scenarios (either simulated via models or coming from actual measurements) as well as reactors of diverse types for concurrently maximizing N(P)P safety and productivity.

The proposed methodology is further amenable to on-line changes in the dataset used for training, with as many GRNN upper-layer node insertions/deletions[13] performed as there are added/removed input-output patterns of detector signals, thus rendering the process custom-made to the current mode (and characteristics) of operation in an on-line manner.

Additionally, the use of concurrent (rather than isolated/independent) inputs has been found to boost GRNN recall as well as prediction accuracy, as has the combination of the individual GRNN responses. The latter point, namely the aggregation of complementary GRNN responses (as derived from different NDs and NF signals, and perhaps even different time-lags, especially for periodic events such as oscillations) in order to further improve the accuracy and sensitivity of detection, constitutes the subject of future research.

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[13] accompanied by the deletion of all the connections emanating from these nodes to the nodes of the lower layer of the GRNN