General Regression Neural Networks for the Concurrent, Timely and Reliable Identification of Detector Malfunctions and/or Nuclear Reactor Deviations from Steady-State Operation

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***Abstract*—The analysis and understanding of the neutron flux (NF) signals of nuclear reactors (NRs) is imperative for ensuring safe and optimal (expressed in terms of minimal fuel use for maximal energy production) on-line NR operation. The NF perturbations are of particular interest, as they provide detailed information concerning the instantaneous changes in NR operation/status. In this piece of research, general regression artificial neural networks (GRNNs) are proposed for concurrently identifying NR deviations from steady-state operation as well as neutron detector (ND) malfunctions in a timely, reliable and efficient manner. On the one hand, the use of (a) raw, minimalistic NF signals and (b) complementary signal encodings – derived from pertinent and limited in size ND configurations – of the problem space, renders the proposed approach timely/efficient, modular as well as flexible. On the other hand, the GRNN characteristics of (i) transparency of construction, (ii) low computational (time/space) complexity of training and testing, (iii) accuracy, consistency and good generalization in the identification of the cause(s) behind deviating-from-normal NR behaviour and (iv) efficient operation and partial only GRNN retraining following modification of the training set, support the use of the proposed methodology. It is envisaged that, by appropriately combining the responses derived from different GRNNs, both accuracy and sensitivity of deviation detection as well as of malfunction localization shall be further improved at minimal additional computational load.**

Keywords—general regression artificial neural network (GRNN), polynomial approximation (PA), semi-parametric spline (SPS), nuclear reactor (NR), neutron flux (NF), NF signal/perturbation/fluctuation, neutron noise (NN), neutron detector (ND), normal/deviating operation, instrumentation malfunctioning, cross-validation (CV)

I. INTRODUCTION

Nuclear reactor (NR) [1] construction is based on considerably detailed, complex models which relate modes of NR operation to macroscopic cross-sections. Determining, predicting and monitoring NR operation requires the formulation of the neutron flux (NF) perturbations/fluctuations [1] of the NF signals, which is implemented – as a rule – via the use of appropriate models that have been formulated in minute detail by experts prior to NR construction. Although such models adequately express the underlying physical phenomena and processes, their derivation is highly complex, as is their understanding and application. It is, thus, advantageous to also resort to expert opinion for directly defining the observed/captured NF perturbations in terms of macroscopic cross-sections during NR operation, as these are captured by neutron noise (NN), namely the fluctuations of NR power over its mean value. By further relating the involved parameters (NN in particular) to the location and characteristics of the driving perturbations, the resulting NR simulations are rendered (a) simple, straightforward and transparent – yet sufficiently detailed – in defining modes of operation and transitions between these modes, as well as (b) accurate in detecting anomalies that might occur during NR operation. Given the system and problem characteristics, it is customary to employ simulated signals, especially those derived from the formulae/models created for investigating (detecting, identifying and rectifying) the problems that may arise during NR operation, with special emphasis being placed on situations/locations where the NR in-core and ex-core instrumentation is scarce.

The focus of this research is upon virtually inverting the NR transfer function – for recovering the anomalies that are responsible for the observed fluctuations –, in order to (i) detect and (ii) identify the cause(s) behind, deviating-from-normal NF signals, as these are caused by abnormal perturbations and/or malfunctioning neutron detector(s) (ND(s)). By further utilizing the shortest signal length from the minimum number of ND signals, the proposed methodology is rendered modular, implementable in a maximally computationally (in terms of both time and space) efficient manner, which is fully capable of on-line response, i.e. properties which are necessary for concurrently providing not only timely and reliable

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[1] caused mainly by (i) two-phase (liquid/gas) coolant flow, (ii) perturbations of physical processes, and (iii) vibration of mechanical components (e.g. fuel assemblies, core barrel, etc.)

decisions on signal validity, but – furthermore – on the identity/cause of the driving perturbation.

This contribution is organized as follows: Section II introduces the general framework (problem definition/ representation and employed signals/methodologies) of NR monitoring and NF anomaly/ND malfunction detection [2]; Section III implements signal verification and prediction via both parametric polynomial approximation (PA) [3], semi-parametric splines (SPSs) [4] and non-parametric general regression artificial neural networks (GRNNs) [5] approaches on data that has been created using established simulation codes (e.g. [6-7]) and handled in its entirety as well as piece-wise (systematically derived from 10-fold cross-validation (CV) [8]), thereby establishing the validity and generalization properties of the three approximations methodologies on the present problem; Section IV critically presents and compares the verification/prediction results, with Section V summarizing the findings and putting forward potential extensions of the present research aims concerning NR monitoring and diagnosis.

II. Problem Framework

A. NN Signals and NDs – S3K Signal Generation

NN signals constitute the prevalent source of information for performing NR system analysis and identification, as well as real-time characterization of the NR operation mode and status. Further to the pure neutron noise part – which is inherent in the NN signal per se and considered crucial for the purposes of system verification as well as for on-line monitoring –, 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, (d) fuel assembly beam mode[2], as well as other temporary and/or harder to define sources of signal distortion, thus effectuating – at times – a significant corruption of the original NN signal to be analyzed. It is important that the various source(s) of NR signal corruption be distinguished and characterized as:

(i) an induced fluctuation or distortion of the NN signal (random or more systematic) which when analyzed, provides important information concerning NR status and operation mode;
(ii) malfunctioning of the ND per se, such as ND bias or intermittencies, which hinders correct NN signal capture in varying ways and to different degrees.

The main aim of the present analysis is to (a) achieve the required (high) level of detection/identification accuracy while (b) minimizing the computational complexity of NN signal validation, thus (c) expediting the identification of diverging NR operation per se as well as of malfunctioning ND(s). To this end, the minimum possible number of NN signals is sought which – combined with the shortest time window – allows swift, reliable and accurate anomaly detection (monitoring) as well as anomaly source identification (classification and localization). It should be mentioned here that, for longer time-windows and/or less stringent on-line operation requirements, wavelets and wavelet multiresolution analysis [9] offer an appealing alternative frequency-based tool; the interested reader is referred to [10] for representative examples and applications.

SIMULATE-3K (S3K) is a state-of-the-art deterministic code which is commonly used by research institutes, utilities and regularity authorities for modelling and assessing the time-dependent three-dimensional behavior of NR cores [11]. The Laboratory of Reactor Physics and Thermal-Hydraulics (LRT) at the Paul Scherrer Institut (PSI) has a long-proven experience in the deterministic safety analysis of the Swiss NRs by utilizing the S3K code. In the framework of the European Horizon 2020 CORTEX project [12], PSI/LRT has analyzed a pressurized water reactor (PWR) core with the S3K code, in the manner described in the OECD/NEA transient benchmark [13], so as to simulate various types of stochastic

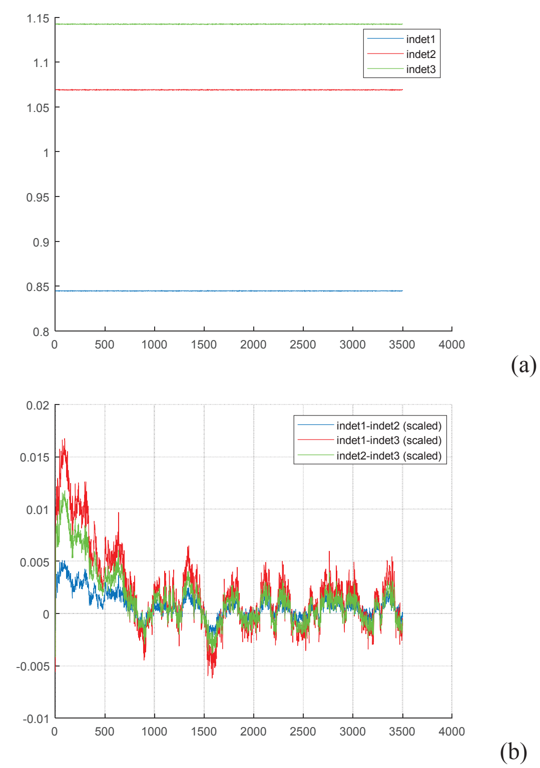


Fig. 1 The original INDET1, INDET2 and INDET3 signals (a), and the pairwise differences of the same signals following their (independent) scaling (b).

[2] which are characteristic of (unique to) the specific NR

perturbations and study their impact on neutron noise behavior. In this work, stochastic perturbations of fuel assembly vibrations are modelled as described in [14] for reproducing NN phenomena.

B. Optimal Combinations and Length of ND Signals

Simulated neutron detectors model the time-dependent NF fluctuations of at various radial and axial locations in the core. For the purposes of efficiency and timeliness of response[3], rather than utilizing all the available ND signals in concert for verifying NN signal correctness, the use of 3-tuples of NDs is proposed. The rationale behind the selected number of NDs for reaching consensus is that, while two NDs are not adequate for the task-at-hand[4], three NDs can be used for competently as well as confidently deriving signal validity. This number of NDs not only simplifies the decision-making process and reduces computational complexity, but – at the same time – boosts the robustness of the final decision in cases of failing NDs and/or erroneous/unexpected NN signals, also accommodating for the far-from-infrequent situation of scarce in- and ex-core instrumentation. For all of these situations, sets of three-tuples of NDs can be used in a reliable and efficient manner for identifying the health-status of the NDs, as well as for decoding the information encoded in the NN signals.

It is important that the pairs of collected NN signals from the three selected NDs be adequately correlated, so that – in case of malfunction – the change (drop) in correlation between one or more pairs of ND-derived NN signals can act as a primary sign of decreasing agreement between ND responses, which can be – subsequently – used for identifying the erroneous NN signal(s) and/or the malfunctioning ND(s). It is also possible to aggregate the decisions of specific (appropriately selected) ND combinations for reaching a consensus-driven global (NR-dependent) decision that takes into account each decision while also exploiting the complementarity of the individual decisions for increasing decision accuracy.

In the following description and demonstration, three signals derived from S3K, named here INDET1 and/or INDET3 (collected by neutron detectors D1 and D3, respectively) are used for demonstrating the prediction of signals INDET2 (collected by neutron detector D2). These signals are shown in Fig. 1(a), with Fig. 1(b) further demonstrating the pairwise relationships between them, as 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 NN signals, and other kinds of fluctuations, trends as well as transients can be observed at different time-stamps and scales (frequencies). Despite their differences (Fig. 1(b)), the signals employed for this investigation 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.

Further to the selection of triplets of signals, the absolute minimal signal length is used for signal verification: 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 – in turn – for setting up the proposed approximation/prediction methodologies[5]. 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 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). 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. 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 ×.

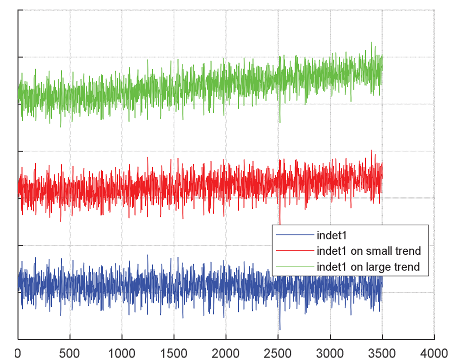
Indet1	Indet2	Indet3	Indet1→ Indet2	Indet3→ Indet2	Indet1 & Indet3 → Indet2
√	√	√	√ (× if Det2×)	√ (× if Det2×)	√ (× if Det2×)
√	√	×	√ (× if Det2×)	×	×
√	×	√	×	×	×
×	√	√	×	√ (× if Det2×)	×
√	×	×	×	×	×
×	√	×	×	×	×
×	×	√	×	×	×
×	×	×	×	×	×

[3] the more detectors used, the more substantiated the decision, yet the higher the computational time/space complexity

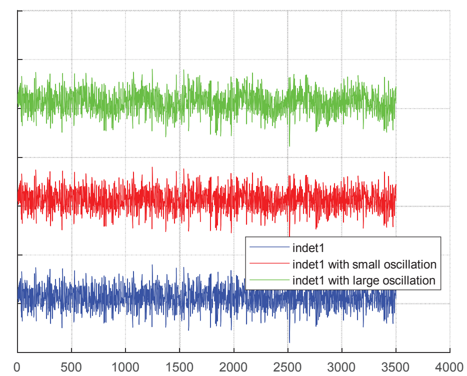
[4] in case of disagreement between a pair of ND signals, it is not possible to establish which ND is misbehaving and/or receiving abnormal information

[5] 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 as short as possible for ensuring low computational time (and space) complexity of operation as well as timeliness of response to abnormal situations

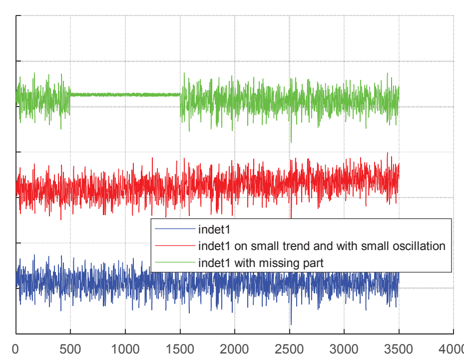
Table I shows a simplified scheme of the effect that (i) erroneous (marked as ×) signals INDET1, INDET2 and INDET3 and/or (ii) malfunctioning (also marked as ×) detectors Det1, Det2 and Det3 have on establishing (a) signal validity and (b) ND (mal)functioning.



(a)



(b)



(c)

Fig. 2 Examples of drift (a), fluctuations (b) and intermittencies (c) applied to the original signal INDET1 (bottom (blue) signal in all the figures).

C. Signals Resulting from Deviations from Normal Operation

The following (perturbed, deviating from normal) signals have been derived from INDET1, INDET2 and INDET3 via the injection/addition/juxtaposition of:

- Drifts, implemented by adding linear trends to the mean value of the original signal; different amplitudes (e.g. small and large trends in Fig. 2(a)) of the slope are used for investigating the capability, as well as the "limit", of successfully retrieving the original signal.
- Fluctuations, simulated by adding sinusoids of different amplitudes and periods to the original signal (e.g. small and large oscillations in Fig. 2(b)) are tested.
- Combinations of drift and oscillations (e.g. middle signal in Fig. 2(c)).
- Intermittencies, where parts of the original signal are missing and are substituted by the (local) mean value of the signal overlaid with white noise of varying standard deviation (top signal in Fig. 2(c)).

D. Prediction Methodologies

Three prediction/function approximation methodologies, covering the entire parametric through to non-parametric spectrum, are used, namely parametric PA, semi-parametric SPSs and non-parametric GRNNs.

While PA analytically determines the optimal polynomial coefficients in order for the input variables to optimally approximate the output variable(s) i.e. to minimize the distance (absolute or squared differences) between actual and predicted outputs, SPSs employ a set of predefined forms which are, subsequently, appropriately selected and combined in a piece-wise manner (i.e. locally over the input/independent variable) so as to optimally approximate the output/dependent variable(s). The non-parametrically trained and operating GRNN, on the other hand, implements (i) direct correspondence between its layers and problem representation (in terms of problem elements and their characteristics/interrelationships/ constraints), (ii) logic-based connections and connectivity-dependent weight assignment, (iii) single-epoch training for (iv) the creation of a non-parametric free-form (purely data-derived and σ-tuned) optimal hypersurface that forms the separating hyperplane between pattern classes.

The GRNN – in particular – constitutes a two-layer compact artificial neural network architecture of straightforward as well as transparent construction, which makes use of a single tunable parameter (the spread, σ). The value of σ determines the area of influence of each training pattern, and consequently shapes the GRNN approximating hyperspace in terms of the available (training) data and the desired continuity of the separating hyperplanes:

- the smaller 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 the interpolation between neighboring training patterns becomes;
- conversely, the larger the value of σ, the more general and impervious to outliers and other extreme training patterns the separating hypersurface becomes, thus, endowing GRNN prediction with robustness and generality at the loss of detail.

The nodes of the two GRNN layers represent:

i. 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 being encoded in a single node of the upper layer of the GRNN.

The connections between nodes are only possible between nodes of different layers and are, furthermore, limited to pairs of nodes (one node from each layer) which are related in a positive or negative manner, expressing whether the appearance of the input feature represented by the connected node of the lower layer is promoted or suppressed by/opposed to, respectively, the training pattern encoded in the connected node of the upper layer. The connection weights are determined independently for each node of the upper layer; while the magnitude (absolute value) of all the non-zero connections emanating from a given node of the upper layer is the same (equal to 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), the (+/) sign of each connection is determined by whether the pair of connected nodes expresses a positive (reciprocal, reinforcing) or negative (opposing) relationship, respectively.

GRNN construction is swift, flexible and can be adjusted in an on-line manner. A single presentation of the training-set patterns is sufficient for setting the optimal form of a non-parametric class-separating hypersurface such that accurate GRNN responses are returned not only to known inputs, but also to novel inputs derived from the same pattern space. By adjusting σ, the generalization potential and robustness to noise of the GRNN is adjusted. For more information on GRNN training, testing and other characteristics, the interested reader is referred to [5]. Concerning GRNN flexibility, it is possible to (a) add a new GRNN node to the upper layer for each novel pattern, with the weights of the new node set in the same manner as for the original training patterns; (b) delete an existing GRNN node of the upper layer if it corresponds to a training patterns that is no longer valid/needed, concurrently removing the connections emanating from the deleted nodes. In both cases (a-b), the approximating hyperplane is automatically adjusted.

The three approximation/prediction methodologies are implemented independently – yet under identical conditions of data normalization and partitioning – for monitoring and concurrently identifying (detecting, classifying and localizing) (a) NR deviations from steady-state operation as well as (b) ND malfunctions. The methodologies are, subsequently, compared in terms of time efficiency and accuracy/reliability.

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

A. Problems Tackled – Data Errors & ND Malfunctions

The three (PA, SPS and GRNN) approaches

- use sets of identical input and output signals for their set-up,
- are tested on identical parts of the dataset according to use-all and 10-fold CV and,
- are, subsequently, compared.

Three distinct cases are investigated in the following, 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 the signals being erroneously recorded;

(3) (some, or all of) the signals per se being erroneous and the NDs operating normally[6].

Case (1) is reported and thoroughly analyzed. The results of cases (2-3) are also reported but not further analyzed in depth, as the effects of malfunctioning ND(s) cannot be sufficiently defined or confirmed by expert consultation[7]. For the present investigation, the distorted signals take on the forms of the corrupted versions described in Section II.C for both cases (2) and (3).

The present 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, with the latter signals representing signal perturbations per se (shown in Tables II-IV(a)) as

[6] in case (3), all the combinations of (i) correct vs corrupted input signals and (ii) detectors operating as expected or malfunctioning (i.e. accurately or erroneously recording the signals) are examined for the prediction of the INDET2 signal

[7] 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 prior to their GRNN encoding and testing

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)

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(Det1×) 0.0467(Det2×) 0.0506(Det3×)
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)

well as signal distortions caused by erroneous capture due to ND malfunctioning (shown in Tables II-IV(b)) for PA, SPS and GRNNs, respectively. In order to standardize GRNN operation on novel data, rather than setting the optimal value of spread (σ) parameter independently for each GRNN, all tests and cross-validation schemes have been performed using the same value of σ (0.1). Such a value confines the resulting GRNN prediction to be evaluated from/confined to "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 proximal training patterns for shaping the GRNN response.

IV. VERIFICATION/MONITORING/PREDICTION EVALUATION AND ANALYSIS

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 appearing not to significantly affect signal predictions. Although oscillations (within the scales tested here) are significantly different to normal operation, they have been found less degrading than either trends or missing signals, implying a marked degree of robustness to such periodic-(shaped) signals. Table II(B) further confirms these findings, showing that periodically malfunctioning NDs are less sensitive than those demonstrating signal drift (for instance) and, thus, more liable to a delayed detection, in other words expressing a more marked deterioration of their detection ability.

SPS operation has been found slightly – yet not consistently – superior to that of PA, demonstrating the advantages of using more degrees of freedom, as these are allowed by the specific piece-wise separating hyper-surface construction methodology over PA[8]. Finally, the GRNN approach has been found clearly superior to both the PA and SPS approaches, demonstrating

[8] it is expected that the potential of SPSs will become clearer under conditions of non-linearity; the same holds for the GRNN

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	0.5922e-07	0.1263e-07	0.3481e-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 (Det1×) 0.0155 (Det2×) 0.0376 (Det3×)
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

(b)

- swift training and perfect recall of the entire dataset for the entire range of values of the spread (σ) parameter, as well as superior prediction under conditions of CV for small (near 0.05) σ values;
- robustness to noise and reliability to missing or otherwise data (when substituted by average or weighted average values) during testing;
- improvement in prediction accuracy when the GRNN predictions of the different input encodings are combined.

V. CONCLUSIONS

The on-line analysis of the neutron noise (NN) from the NF signals which are continuously collected at nuclear reactors (NRs) is required for ensuring safe as well as efficient operation. The recorded NN perturbations have been used since the installation of the earlier NRs for monitoring and prediction purposes, thus providing precise information concerning the instantaneous (relative) changes in NR operation/status and, concurrently, the identification (detection, classification and localization) of (i) NR deviations from steady-state operation as well as (ii) neutron detector (ND) malfunctions, in an on-line manner.

In this piece of research, a range of parametric, semi-parametric and non-parametric methodologies has been put forward for detecting and localizing deviations from steady-state (or otherwise scheduled) NR operation, as well as for identifying ND malfunctions using the available NF/NN signals. Aiming at robustness, timeliness, modularity as well as low computational complexity, rather than using all the available ND signals in concert, the use sets of 3-tuples of ND signals has been put forward, thus simplifying and modularizing the decision-making process, while – concurrently - increasing the robustness of the final decision via the combination/consensus of PA/SPS/GRNN decisions. Furthermore, the collection and subsequent aggregation of decisions from selected 3-tuples of NDs has been proposed and found to promote consensus-driven decisions that take into account each decision as well as the complementarity of the individual decisions in a most efficient as well as robust manner.

The investigated approaches accomplish modularity and flexibility of operation by employing (a) raw NN signals as their source of information and (b) complementary NN signal encodings – derived from pertinent ND configurations – of the problem space. While all the tested methodologies have been found capable of providing consistently valid responses, the semi-parametric SPS has been found clearly superior to PA, with the use of GRNNs established as the most satisfactory methodology 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,
(iii) ease of adaptation to new data and to changing operating (NR-construction, e.g. ND configuration) conditions; the on-line changes in NR operation are directly reflected on the GRNN(s), via as many GRNN upper-layer node insertions/deletions [9] implemented as there are added/removed input-output patterns of the detector signals, rendering the process custom-made to the current mode (and characteristics) of operation in an on-line manner, implemented exclusively via the observed NR operation (as expressed by NF/NN signals);
(iii) superior accuracy in the identification of the cause(s) behind deviations from normal/scheduled NR operation; the latter remains an open topic that is worthy of further investigation in terms of the optimal aggregation of GRNN responses.

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

The non-parametric nature of the proposed GRNN has demonstrated the potential of developing a tailor-made data-driven (rather than a more rigid system based on a specific NR 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) for the given NR as well as easily transferred to/adapted for NRs of diverse types for concurrently maximizing NR safety and productivity while also satisfying the requirements of on-line monitoring, NR analysis, regime identification, transient detection and evaluation as well as anomaly isolation among others. The proposed methodology is further amenable to the use of varying: (i) time-window lengths, which can be adjusted appropriately based on conditions of NR operation and/or signal characteristics, (ii) means of combining the individual GRNN responses for accomplishing maximal accuracy, (iii) the minimal necessary duration (length/time window) of data collection based on the issue to be tackled as well as its location.

Additionally, the use of concurrent in time (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 selected, complementary GRNN responses (as derived from different NDs and NF signals, and perhaps even different time-lags, especially for periodic events such as oscillations) constitutes the subject of future research for further improving the accuracy and sensitivity of detection.

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