

The Combination of

State-of-the-Art <u>Signal Processing</u> and the <u>Computational Intelligence</u> Paradigm for the Efficient, Accurate and Robust Processing of <u>Nuclear Reactor Data</u>

CORTEX Workshop

Advanced signal processing methods and learning methodologies applied to the monitoring of NPP reactor conditions 20 February 2019, Řež

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The Natural (Living) Intelligence Paradigm

All living organisms use (some kind of) intelligence in order to survive and propagate/multiply

Prerequisites of survival (fight or flight) are to:

- adapt in order to increase survival potential (non-stationary, time-varying "system")
- find water, acquire food, remain safe, discover/construct a shelter (weather, fire, human/animal attacks)
- cross land, rivers and seas to escape danger (counter-act climatological/environmental, predators)
- discover/adapt/devise/create "survival" and "warfare" tools/procedures (ally bonding & enemy defense/offense) act re-act pro-act

Take advantage of/manipulate (turn "bad" to "good") *.*, e.g. fire, water, wind, animals, terrain/morphology

Invent effective defense and offence weapons, (moats, walls, labyrinths) tactics (algorithms)

Develop a growing body of knowledge (oral and written) in arts and sciences, keep records (dataset creation), devise calculating systems, computers (direct transfer of human/animal, when a particular species is superior) of actions/procedure/intelligence to the creation and use of (progressively, all the more) autonomous "tools", both animate (trained wolves/dogs/eagles) and inanimate (constructed pulleys, cranes, as well as computer programmes) which are superior for the task-at-hand. Develop intelligent inanimate objects/systems/devices (automata/αὐτόματα, seemingly "acting of their own will") of interest from the early days of civilization https://en.wikipedia.org/wiki/Automaton



Fight-or-flight response

123RF.com

The Artificial, Computational, Swarm Intelligence (AI, CI, SI) Paradigms

Express the elements of the problem (and solve the problem) at different level of representation (symbolic, subsymbolic, hyper-symbolic):

Al symbols (symbolic level), where each symbol constitutes a core element of the problem that can take on a number of values and the states (including the initial and final state) constitute sets of values of these symbols. Going from the initial to the final (solution) state is implemented via symbol manipulations that cause elementary (and valid) steps/transitions from the current to the next state of the problem, with the selected transition leading the closest to/ towards the aim/solution/end-state. Search, constraint propagation and satisfaction, inference (expert) systems etc. implement different Al methodologies which are serially implemented (no parallel processing). Al encounters bottleneck issues when the problem size and/or problem complexity rises (combinatorial explosion of alternatives).

CI sub-symbols (sub-symbolic level), which come together to represent the symbols of AI. The manipulation of the elements of the problem is implemented as parallel distributed processing of the sub-symbols. The lower (than in AI) level of representation is inspired by the 10¹⁴ neurons in the brain promotes flexibility and improved level-of-detail in the state-by-state transitions, adding robustness in cases of partly missing and/or erroneous information (best-possible rather than no-solution) and allowing the concurrent investigation of alternative paths (parallel processing).

SI simple agents (super-symbolic level), e.g. ant colonies or swarms of bees, which represent potential solutions (as problem states rather than solutions per se) and collaborate in their search for food sources (solutions) via processes such as ant pheromone laying and bee dancing in order to convey information concerning food source location and quantity to the entire population. Each agent acts independently, yet takes into account the information (e.g. pheromone concentration) along the various paths. A shorter path is faster to traverse, thus is laid with more pheromone, inviting more agents to follow it (reinforcement). The communal mobility gradually (a) determines the best nearest foodsource, (b) converges to the shortest path from the nest/hive etc. to this foodsource, (c) promotes efficient response (path alterations) to changes in the environment (e.g. path obstruction, foodsource depletion).



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Interest in key-issues of N(P)P operation, namely

- * control
- diagnostics and fault detection
- * monitoring, N(P)P operations
- proliferation and resistance applications
- sensor and component reliability
- ✤ spectroscopy
- fusion supporting operations

Selection of the pertinent/appropriate CI methodologies, namely among

- artificial neural networks
- fuzzy logic (inference systems)
- genetic algorithms/programming, evolutionary strategies



Data (pre-)Processing and Encoding/Representation

Data/signal visualisation, pre-processing and analysis

cannot

the dataset expresses the problem (characteristics/ states): other than "cleaning" detrending, removing 100% known-to-be errors etc., DO NOTTOUCH!

- exceed/improve upon the data, hence valid results cannot be obtained from an erroneous dataset

can

- uncover errors in data which degrade the operation of any model (parametric, semi-/non parametric) e.g. out-of-range values, infeasible combinations of values for (cor)related parameters (e.g. male and pregnant),
- isolate transient characteristics (e.g. transients and trends)
- evaluate statistics of the data (distribution, mean value, standard deviation, skewness, level and nature of noise)
- perform data denoising, normalization, subsequently fill-in missing values (variety of methods).

Statistics operations, e.g. cross-correlation of the input data reveals repeated information (which skews/biases the dataset statistics and characteristics).

Feature extraction or selection may also be appropriate as a complementary step for reducing the computational burden and skewed statistics that are caused by the redundant/repeated information.

cs.gmu.edu/~carlotta/teaching/INFS-795-s05/readings/Classification_1.ppt

Data (pre-)Processing and Encoding/Representation

Linking with George Alexandridis' presentation

Data/signal Processing (Fourier analysis, wavelets)

Fourier transform: the signal is represented as a sum of sinusoids, thus revealing the frequencies which are inherent in the signal; appropriate for LTI systems (also for other systems, yet without the potential of fully being able to characterize the underlying phenomena)

Wavelets extract the frequencies occurring at different times (temporal frequency extraction). Different prototypical shapes (mother wavelets) can be used, depending on the shape that it is of interest to identify and isolate/detect in the signal; the better the match (similarity) between signal and mother wavelet, the better the detection/signal decomposition into scaled and translated versions of the mother wavelet. Appropriate for more general kinds of systems (not necessarily LTI)



Neural networks (BP)

Biological

Artificial



"learn" from known inputoutput pairs (training set) test on the same and unseen data validation, test (n-fold crossvalidation)





Neural networks (SOM)

Biological

homunculus

Artificial



Bob/Jim/Mary horse/dog/cat beer/water meat/bread runs/walks works/speaks visits/phones buys/sells likes/hates drinks eats much/little fast/slowly often/seldom well/poorly	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15	Sente 1-5-12 1-5-13 1-5-14 1-6-12 1-6-13 1-6-14 1-6-15 1-7-14 1-8-12 1-8-2 1-8-3 1-8-4 1-9-1	ence Pat 1-9-2 1-9-3 1-9-4 1-10-3 1-11-4 1-10-12 1-10-13 1-11-14 1-11-12 1-11-13 1-11-14 2-5-12 2-5-13	terns: 2-5-14 2-9-1 2-9-2 2-9-3 2-9-4 2-10-3 2-10-12 2-10-13 2-10-14 2-11-4 2-11-12 2-11-13 2-11-14	Mary likes meat Jim speaks well Mary likes Jim Jim eats often Mary buys meat dog drinks fast horse hates meat Jim eats seldom Bob buys meat cat walks slowly Jim eats bread cat hates Jim Bob sells beer (etc.)





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Fuzzy Logic



- two-dimensional for two colours (red and yellow)
- three-, ??? dimensions for more colours
- continuous membership values (not steps of 0.5, as shown here)





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PRESENT FOCUS: the means of tackling the problem at hand, <u>representation of the problem</u>



Artificial neural networks for neutron source localisation within sealed tanks, Annals of Nuclear Energy, Vol. 23, No. 18, pp. 1477-1488, 1996 SAFEGUARDS & ANNs

non-destructive localisation of even plutonium isotopes

in sealed tanks simulated data tanks placed in a well counter (I) which is surrounded by 12 neutron detectors (II) highly non-linear detector responses as a function of the angle between neutron detector and corresponding isotope source location to train BP ANNs

inputs: sets of 12 filtered Fourier transformed detector responses at three distances and four noise levels (2.5, 5, 7.5 and 10%) outputs: even plutonium isotope locations (angle and distance from the centre) majority (mean of two closest) and median (middle) BP ANN responses for angle and distance prediction



System identification during a transient, Annals of Nuclear Energy ,Vol. 25, No. 6, pp. 465-480, 1998 MONITORING & WAVELET MULTIRESOLUTION ANALYSIS

For steady state operation of N(P)s, the fast Fourier transform (FFT) is adequate for identifying the system characteristics.

During a transient, FFT fails. It is shown that wavelet multiresolution analysis is capable of uncovering the signal (i.e. isolating the transient) by the double application of denoising, using as threshold for hard thresholding of the wavelet coefficients std(signal) for deriving signal1 and std(signalsignal1) for deriving signal2.

The double application of hard std-based thresholding of the wavelet coefficients practically eliminates the edge effects, thus saving up to 50% of the signal length that would otherwise be unusable for the purposes of signal/system analysis.





On-line estimation of transit time using artificial neural networks, Nuclear Science and Engineering, Vol. 130, No.1, pp. 113-127, 1998 **MONITORING & ANNs**

> **Estimation/monitoring of the transit time of** the coolant in coolant pipes of N(P)Ps is - necessary for establishing normalcy of the coolant flow: - implemented via the cross-correlation (or cross-power spectral density) of the neutron noise signals at pairs of axially separated neutron detectors (NDs) (delayed, off-line)

> > For the same pairs of signals, the interactive activation/competition (IAC) ANN provides on-line, robust (especially when transit-time varies),

DAC ANN

BP ANN

competitive

Appending a **BPANN** to the competitive IAC and its mirror interactive IAC ANN allows for learning and predicting decimated time.



interactive IAC ASS

enty at

(-0.3, 0.3)



3,[1]

0

0

Ο

On-line stability monitoring of BWR's using artificial neural networks, Annals of Nuclear Energy, Vol. 26, No. 14, pp.1287-1302, 1999 MONITORING & ANNs







Estimate the decay ratio and other stability parameters of the point, 2nd, 3rd and 4th order systems from short records, for providing an on-line indication of BWR stability

SNR=20

SNR=20

(b)

(e)

The required number of inputs depends on the order of the system (point: 1st min; 3rd order: 1st min, 1st max; 4th order 1st, 2nd, 3rd min) etc.

Use the shortest possible time-windows for on-line estimation

Only evaluate the CCF at the specific time-lags

SNR-40

SNR=40

0.5 0.8 0.7 0.8

(a)

(d)

Robustess to noise



SNR-10

(c)

(f)

Instability localization with artificial neural networks, Annals of Nuclear Energy, Vol. 29, No. 3, pp. 235-253, 2002 MONITORING/DIAGNOSTICS & ANNs

2-D bare reactor model with a one neutron-energy Instability modeled by a variable strength absorber (point-source) in a two-dimensional bare reactor model with one neutron-energy group. Exercise in simplicity:

Use:

- a simple (simplified) model of the reactor to train/validate the BP ANN, the standard model to test
- four well-spaced, yet away from the boundaries of the reactor, detector responses at positions that are symmetrical to the centre of the reactor
- six response-ratios as ANN inputs, derived directly from the neutron noise signals (uncomplicated, swift pre-processing), reduced pattern complexity

- two ANN outputs (the X- and Y-coordinates of instability), unlike previous approaches employing hundreds of outputs (one for each fuel assembly)

BP ANN trained on the simplified model, tested on the full model:

- the architecture is independent of the number of possible locations of instability.
- few patterns of low complexity used for ANN training
- a measure of confidence (estimated error) assigned to the prediction, related to the distance of the proposed location of instability from the centre of the reactor.

Following the initial localisation, the final decision on the location of the instability is derived by (i) excluding the prediction of the BP ANN dedicated to the quadrant into which the instability is predicted and (ii) re-evaluating the location (using the other three predictions only)



A non-stationary signal correlator for on-line transit time estimation, Annals of Nuclear Energy, Vol. 29, No. 11, pp. 1299-1313, 2002 MONITORING & ANNs



The interactive activation-competition artificial neural network (IAC ANN) provides an estimate of the current transit time for each incoming pair of signal values (BWRs)

Transit time monitoring is accomplished reliably and in an online manner for both constant and oscillating flow regimes, i.e. for both stationary and non-stationary signals

The IAC ANN is robust to the presence of local and global components as well as to the presence of white uncorrelated noise

Some details:

Filtering. It is a good idea to discard the decisions of the outer two nodes (one on each side) of each ANN in order to avoid erroneous decisions in cases where the actual transit time is just outside the range supported by the ANN (in which case the corresponding outer node is the "best loser" rather than the winner) An estimation of the transit time is made at each time step by considering the recent history of the ANN decisions (from which the current final estimation cannot significantly deviate



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On-line channel instability localisation with fuzzy rule-based systems, Annals of Nuclear Energy, Vol. 31, No. 7, pp. 773-788, 2004 MONITORING & FUZZY LOGIC

A fuzzy rule-based system is implemented for on-line channel instability localisation within a nuclear reactor

A limited number of detector responses has been used for setting up the system, where the signals have been obtained from a rough simulation of the reactor and correspond to a restricted number of channel instability locations

The tests involve novel channels of instability, which are obtained from a more detailed simulation and cover an extensive number of channel instability locations

The proposed methodology has been found capable of accurately, robustly and efficiently localising channel instability



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On-line signal trend identification, Annals of Nuclear Energy, Vol. 31, No. 14, pp. 1541-1553, 2004 MONITORING & ANNs SOM categorization accuracy for varying SNR levels of white noise; artificial test signals

SNR Overall Errors (%) accuracy (%) A 1x30 self-organizing map (SOM) From (B) to From (C) to From (A) to is employed for on-line signal trend (A) **(B)** (C) (A) (C) **(B)** identification ∞ (no noise) 100 0 0 0 0 0 0 100 99.64 0.080.11 0.110.06 0 0 50 99.37 0.110.25 0.19 0 0.080 **Trends** are 25 98.72 0.270.440.46 0.110 0 categorized at each incoming 15 97.7 0.410.96 0.660.27 0 0 signal point as steady-state, 10 96.65 0.76 1.280.93 0.38 0 0 increasing and decreasing 5 93.73 1.72 2.181.610.73 0 0.03 further classified according to SOM classification accuracy for varying SNR levels of white noise; artificial test signals characteristics such signal shape CD TD A1 1 . 1 1:0 (0/) and rate of change

The implementation is found especially robust to the presence of white noise

SNR	Absolut	Absolute node shifts (%)							
	0	1	2	3	4	5	6	7	8
100	97.55	2.32	0	0.05	0.05	0.03	0	0	0
50	95.03	4.73	0	0.05	0.05	0.14	0	0	0
25	89.69	9.82	0.03	0.11	0.08	0.22	0	0.05	0
15	82.94	16.09	0.16	0.16	0.11	0.46	0	0.08	0
10	74.32	23.47	0.85	0.19	0.33	0.71	0.08	0.05	0
5	55.81	35.38	5.63	0.98	0.68	1.17	0.16	0.16	0.03



Parameter estimation during a transient – application to BWR stability, Annals of Nuclear Energy, Vol. 31, No. 18, pp. 2077-2092, 2004 MONITORING/SYSTEM IDENTIFIATION & WAVELETS

System parameter estimation is of the essence for monitoring and system identification/verification.

During transient operation, the parameters change rapidly rendering the system time-varying, whereby classical signal processing techniques are not applicable

Wavelet multi-resolution analysis, which can be used under such conditions, is implemented, followed by the selection of salient wavelet coefficients and the application of classical signal processing techniques for providing valid short-term estimates of the system parameters of interest

The use of highly overlapping time-windows aids in more closely monitoring the gradual changes in system parameter values





Non-invasive on-line two-phase flow regime identification employing artificial neural networks, Annals of Nuclear Energy Vol. 36, No. 4, pp. 464-469, 2009 SYSTEM IDENTIFICATION & ANNS

Non-invasive on-line identification of BWR twophase flow regimes is investigated using real neutron radiography images of coolant flow recordings as inputs

Feature extraction utilising simple and directly computable statistical operators, namely mean pixel intensity, of (a) the entire image, (b) each row and (c) each column.

The extracted features are used as inputs to an ensemble of self-organizing maps (SOMs), which generates the different classes without supervision, based on feature similarity of the corresponding images. Swift and accurate classification of each image into its corresponding flow is performed, without the need to define the number of distinct classes or supply training vectors for each class.

Worst-case accuracy and confidence in the SOM decisions; fifth cycle of the crossvalidation process.

SOMs	SOMAB		SOMAC		SOM en semble	
flow regime	Accuracy (%)	Confiden ce	Accuracy (%)	Confidence	Accuracy (%)	Confiden
Bubbly	81,63	0,9029	83,67	0,7523	87,76	0,8663
Slug	91,84	0.8554	87,76	0.9381	95,92	0.8650
Chum	100	0,9847	95,92	1	100	0,9764
Ann ular	100	1	100	1	100	1



Examples of radiography images: bubbly,

slug, churn and annular flow-regimes





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A general regression artificial neural network for two-phase flow regime identification, Annals of Nuclear Energy Vol. 37, No. 5, pp. 672-680, 2010 MONITORING/SYSTEM IDENTIFICATION & ANNS

A general regression artificial neural network (GRNN) is proposed for the identification of the two-phase flow that occurs in the coolant channels of BWRs. The utilization of a limited number of image features derived from radiography images affords the proposed approach with efficiency and non-invasiveness. Additionally, the application of counter-clustering to the input patterns prior to training accomplishes an 80% reduction in network size as well as in training and test times. Cross-validation tests confirm on-line flow regime identification accuracy.





A fuzzy inference system for two-phase flow regime identification from radiography images, International Journal of Nuclear Energy Science and Technology, Vol. 5, No. 4, pp. 321-334, 2010 MONITORING & FUZZY LOGIC







	minute		bubbly
If the mean image intensity is	small	then the flow regime is	slug
If the mean mage mensity is a	medium	> men me now regime is <	churn
	large		annular

	[[0	~ 0.235)		bubbly flow
If the EIC output falls within	[~ 0.235	~ 0.405)	then the desision is	slug flow
If the F15 output fails within a	~ 0.405	~ 0.665)	> then the decision is -	churn flow
	[~ 0.665	1]		annular flow

Decision accuracy (%)	Random cross-validation	Piece-wise cross-validation
Pooled Results		
correct decisions	92.3057	91.9857
overestimations	5.5232	5.7221
underestimations	2.1711	2.2922
Bubbly Flow		
correct decisions	100	98.3673
overestimations	0	1.6327
underestimations	N/A	N/A
Slug Flow		
correct decisions	81.1265	79.5673
overestimations	10.1581	11.7094
underestimations	8.7154	8.7233
Churn Flow		
correct decisions	88.7510	88.3755
overestimations	10.5174	10.8213
underestimations	0.7316	0.8032
Annular Flow		
correct decisions	99.1835	99.8
overestimations	N/A	N/A
underestimations	0.8165	0.2



Thank you!





Thank you

