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Applying the Computational Intelligence Paradigm to Nuclear Power Plant Operation:
A Review (1990-2015)

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ABSTRACT

In the guise of artificial neural networks (ANNs), genetic/evolutionary computation algorithms (GAs/ECAs), fuzzy logic (FL) inference systems (FLIS) and their variants as well as combinations, the computational intelligence (CI) paradigm has been applied to nuclear energy (NE) since the late 1980s as a set of efficient and accurate, non-parametric, robust-to-noise as well as to-missing-information, non-invasive on-line tools for monitoring, predicting and overall controlling nuclear (power) plant (N(P)P) operation. Since then, the resulting CI-based implementations have afforded increasingly reliable as well as robust performance, demonstrating their potential as either stand-alone tools, or - whenever more advantageous - combined with each other as well as with traditional signal processing techniques. The present review is focused upon the application of CI methodologies to the - generally acknowledged as - 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, as these have been reported in the relevant primary literature for the period 1990-2015. At one end, 1990 constitutes the beginning of the actual implementation of innovative, and – at the same time – robust as well as practical, directly implementable in H/W, CI-based solutions/tools which have proved to be significantly superior to the traditional as well as the artificial-intelligence-(AI)derived methodologies in terms of operation efficiency as well as robustness-to-noise and/or otherwise distorted/missing information. At the other end, 2015 marks a paradigm shift in terms of the emergent (and, swiftly, ubiquitous) use of deep neural networks (DNNs) over existing ANN architectures and FL problem representations, thus dovetailing the increasing requirements of the era of complex - as well as Big - Data and forever changing the means of ANN/neuro-fuzzy construction and application/performance. By exposing the prevalent CI-based tools for each key-issue of N(P)P operation, overall as well as over time for the given 1990-2015 period, the applicability and optimal use of CI tools to NE problems is revealed, thus providing the necessary know-how concerning crucial decisions that need to be made for the increasingly efficient as well as safe exploitation of NE.

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1. INTRODUCTION

Nuclear energy (NE, Weinberg, 1994) amounts to the energy that is required in order for an atom to retain its stability, i.e. for the protons and neutrons that comprise the nucleus of the atom to remain bound to each other. NE is released when

(1) the nucleus of an atom is split into smaller nuclei (nuclear fission, NFi),
(2) the nuclei of two or more atoms are integrated into a larger nucleus (nuclear fusion, NFu),

where, in both cases, the released neutrons of the nuclei of the atom(s) involved in the process are vital not only for producing NE, but also for sustaining the chain reaction. In a nutshell:

(1) the difference in mass (and, thus, energy) between the original and resulting nuclei causes the release of significant amounts of NE (especially when compared to the size of the interacting elements), which - following collection and conversion - can be used for turning turbines, and consequently driving generators to produce electricity [1];
(2) the neutrons released from these nuclei sustain the NFi/NFu phenomena.

The practical exploitation of NE has become of particular interest since the last century[2], with - to date - NFi constituting the main means of energy production. The last 20 years have further brought about a shift in nuclear (power) plant (N(P)P) construction and operation, with the focus moving away from building new and towards maintaining existing N(P)Ps. Consequently, special emphasis has been placed upon the need for (i) comprehensive plant life management (PLiM) and (ii) cost-effective as well as reliable instrumentation & control (I&C), both of which are crucial not only for avoiding a forced shut-down due to unavailability, but also for maintaining optimal functionality of the ageing N(P)Ps.

Control, diagnostics and fault detection, monitoring, N(P)P operations, proliferation and resistance applications, sensor and component reliability, spectroscopy and – finally - fusion supporting operations have been established as key-issues of safe, maximally efficient real-time adjustable N(P)P operation (Ma & Jiang, 2011). Complementary to the traditional signal and image/sound processing techniques that have been applied to these key-issues, the computational intelligence (CI) (Pedrycz, 1997) paradigm - which was put forward in the early 1990s as a set of computationally effective, adaptive, resistant-to-noise as well as to missing and/or partly erroneous information - has provided alternative on-line/real-time, robust, non-invasive methodologies for monitoring, controlling and predicting N(P)P operation. For the last 25 years, the resulting CI-based implementations and applications have afforded prompt, reliable as well as robust response to these key-issues, thus demonstrating the potential of CI either as a superior stand-alone tool, or - whenever advantageous - in combination with traditional signal and/or image processing/analysis techniques.

The present review communicates the application of CI methodologies to the aforementioned N(P)P key-issues, as reported in the relevant primary literature of the major publication and dissemination media (listed in alphabetical order):

(1) Annals of Nuclear Energy (ANE), published by Elsevier,
(2) Fusion Science and Technology (FST), Nuclear Science & Engineering (NSE) and Nuclear Technology (NT), all three published by the American Nuclear Society (ANS), and
(3) Progress in Nuclear Energy (PNE), also published by Elsevier

journals for the period 1990-2015. A crucial decision has been made not to extend the present review beyond 2015 as the transition from 2015 to 2016 brought about an important paradigm shift in terms of CI tools used, namely in the application of deep neural networks (DNNs, Bengio (2009)) for upscaling the proposed solutions to significantly harder, more complex situations as well as to the concurrent efficient processing of significantly more numerous data, something that was not considered possible till then. By exposing the most representative and/or successful CI-based tool(s) for each key-issue, an understanding of the particular strengths of the used tools - as relating to NE - is afforded. It is observed that, despite the superior performance (solutions and implementations) offered by CI-based implementations over more conventional signal processing methodologies (which has more often than not been demonstrated on real data) for the specific period, the resulting CI-based implementations are – as a rule - not translated into stand-alone practical/commercial tools.

The remainder of this review is organised as follows: Section 2 describes the key-issues of N(P)P operation that are discussed in more detail in the following sections, followed by a brief description of the CI paradigm and the main methodologies that appear in the relevant literature for tackling each key-issue; Section 3 tabulates and critically reviews the research and trends reported in the primary literature for the various combinations of N(P)P key-issues and exponents of the CI paradigm, as observed for the period 1990-2015; finally, Section 4 summarises the findings, proposes future directions and concludes the review.

2. N(P)P OPERATION AND THE CI PARADIGM - A BRIEF EXPOSITION

2.1. N(P)P Energy Production and Maintenance/Safety Issues

N(P)Ps produce around 15% percent of the world's electricity, thus significantly surpassing the alternative - conventional (fossil fuels such as petroleum, coal and gas) as well as renewable (solar, wind, wave etc.) - means of energy generation, while further demonstrating significant advantages in terms of operational cost, efficiency and cleanliness. However, N(P)P monitoring and scheduling must be vigilantly managed, while – even more importantly - nuclear fuel (both operational and exhausted) must be carefully handled and guarded as it remains radioactive for long and may seriously damage the flora, the fauna and the environment if released or mishandled.

2.2. The CI Paradigm

Historically, the artificial intelligence (AI) paradigm (Jackson, 1985) constitutes the first mature step towards endowing computer programmes with intelligent-like behaviour. AI uses a symbolic representation (Newell & Simon, 1976) of the problem and employs techniques such as search, constraint propagation and rule-based inference for providing solutions (appropriate combinations of compatible values for the sets of symbols which collectively represent both the problem-at-hand and its states) to complex problems that cannot be tackled via standard computer programming. Although AI achieved significant breakthroughs in the 1970s and early 1980s - with a variety of AI-based problem solving methodologies being still applied to diverse domains (including NE), bottleneck problems soon became apparent as the scale of the problems increased, rendering the attainment of a solution an extremely time- and resource- consuming process.

Consequently, a paradigm shift toward swarm intelligence (SI, Bonabeau et al., 1999) and CI (Siddique & Adeli, 2013) occurred; by operating at the hyper- and sub-symbolic levels (Stamou et al., 1999), both SI and CI, respectively, overcome the AI-related bottlenecks to a significant degree.

SI is based on the collaboration and communication between simple "agents" where, although each agent is marginally capable of independently finding a solution to the problem at hand, the implicit communication between agents helps the ensemble to improve upon their individual solutions and to converge upon a (near-)optimal solution to the problem. Two representative exponents of SI are:

(a) Ant colony optimisation (ACO, Dorigo & Stützle, 2004), where the pheromone-based aspects of (i) trail creation by each ant of the colony, (ii) indirect communication between the ants of the colony via the levels of pheromone concentration deposited over the foraging area and (iii) gradual pheromone trail evaporation, are exploited during foraging of the ant colony for improving its food-collection performance. The repeated foraging/foodsource discovery of each ant and the concurrent pheromone laying and evaporation promote convergence of the entire colony upon a/the shortest trail to the closest and/or richest foodsource[3].

(b) Particle swarm optimization (PSO, Kennedy & Eberhart, 1995), where a swarm of "particles" navigates a given space in search of foodsources. Although along similar lines to ACO, the core of PSO is particle positioning: each movement of every particle is concurrently influenced by the (currently) best[4] positions of (i) each particle and (ii) the entire swarm, whereby the movements of (each member of the) entire swarm collectively implement convergence to the shortest path to the richest foodsource.

Complementary to SI, the aim of CI is to mimic the means by which crucial aspects of natural (mainly - but not exclusively - human) intelligence are implemented. The focus is upon both form and function, with inspiration provided by the distributed, redundant and dynamic nature of information encoding in the brain and central nervous system, thus promoting (a) the on-line adjustment of its behavioural and structural characteristics in order to better fit the changing environment; (b) generalization capabilities and robustness, which collectively allow the accurate, efficient/swift reaction - and avoidance of bottlenecks - under conditions of noisy, partly erroneous (conflicting) and/or missing input information, as well as under partial damage of the brain or the central nervous system. These aspects of intelligence (and optimal survival) are translated into the following three main CI paradigms:

(A) Artificial neural networks (ANNs) (Rumelhart & McClelland 1987), where natural "intelligent" function emerges from the simulation of the form and function of groups of interconnected/interacting biological neurons that are located in the brain and the central nervous system. Information is concurrently learnt and encoded in: (i) the collective activation patterns (firing levels or rates) of ensembles of neurons (rather than in the neurons per se); and (ii) the strengths and signs of the connections between neurons. A significant variety of ANN architectures has been implemented, simulating different aspects of biological neural ensembles that are found in various areas of the brain and/or in different biological organisms, including (in alphabetical order)

- Auto-associative ANNs (Kramer, 1992)
- Back-propagation (BP) ANNs (Rumelhart et al., 1986) - also known as feedforward ANNs or multi-layer perceptrons (MLPs)), including its variants and extensions
- Cellular NNs (CNNs, Chua & Yang, 1988)
- Deep NNs (DNNs, Bengio, 2009)
- Dynamic NNs (DynNNs, Sinha et al., 2000)
- General regression NNs (GRNNs or GRANNs, Specht, 1991)
- Hopfield NNs (Hopfield, 1982)
- Interactive activation & competition NNs (IAC ANNs, McClelland & Rumelhart, 1981)
- Linear vector quantization (LVQ, Kohonen, 1995)
- Radial basis function ANNs (RBFs, Broomhead & Lowe, 1988)
- Recurrent NNs (RNNs, Pearlmutter, 1989)
- Self organising maps (SOMs, Kohonen, 1982)
- Spiking NNs (SNNs, Gerstner, 2001).

(B) Robust and accurate reasoning/decision-making accomplished via fuzzy logic (FL) inference systems (FLIS, Zadeh, 1965). Unlike the - standard in mathematics and logic - crisp representation of a variable that stands for a given concept or property[5], FL assigns a degree of belief (i.e. graded membership) to the variable. By introducing degrees of acceptance of/belief in any notion, the resulting problem representation/framework mimics biological intelligent reasoning and behaviour. Especially when such a fuzzy representation spans over a number of interrelated concepts, the processes of inference and deduction become especially robust, general and flexible in expressing as well as in exploiting partial (non-crisp) and/or noisy/partially missing concepts/notions, very much alike to those expressed in natural language. Additionally, by being more human-like in expression and, thus, also more easily understood, this kind of inference is acceptable by humans (e.g. N(P)P operators).

In more detail, and unlike crisp logic, FL expresses the degree (of membership) to which the property represented by a given variable is true in a graded (fuzzy) manner, communicated by a value within the interval [0 1], where the degree of membership of the variable over the entire range of values is usually continuous and may take a variety of shapes, depending on the problem definition and the properties of the variable[6].

FL uses fuzzy inference rules (of the IF-THEN form), which may be either of the Mamdani (Mamdani, 1974) or of the Takagi-Sugeno (Takagi & Sugeno, 1985) type, where (for more information, the interested reader is referred to Zadeh (1965)):

- The input(s) to a fuzzy rule of either type of fuzzy inference must be fuzzy - or fuzzified, if originally crisp - variable(s)
- T-norms are used for combining the fuzzy variables in the fuzzy rules via fuzzy "and", "or" and "not" logical operators
- The outputs (consequents) are fuzzy variables for the Mamdani type and crisp values for the Takagi-Sugeno type

The choice of type of fuzzy rule used by a FLIS depends on the characteristics of the problem as well as the desired form of the final output. Some important distinguishing characteristics between the two types of FLIS are that:

(1) the Mamdani-type is easier to interact with and the fuzzy output is easier to understand, whereas the Takagi-Sugeno-type requires significant know-how for setting the T-norm coefficients
(2) the Takagi-Sugeno-type is more efficient than the Mamdani-type, with the continuous output space being not only directly optimizable but also more easily amenable to analysis (and understanding of the underlying phenomenon and its characteristics
(3) Genetic algorithms (GAs, Goldberg, 1989) are inspired by the ability of living beings to adapt to the changing conditions of their environment, e.g. temperature, humidity, radiation, salinity, predators, surrounding flora and fauna etc. Individuals with traits that render them better equipped to protect themselves, to attain food and to appeal to the other sex, tend to live longer and to produce more offspring. The traits promoting longevity and reproductive superiority are – more often than not - passed on to their offspring, who either continue to change over time in order to adapt to changing conditions, or are superseded by other (currently) "fitter" individuals of the population. The CI-derived survival-of-the-(currently)"fittest" paradigm is translated into GAs as a means of swiftly attaining a (near-)optimal solution to a given problem. While crossover (combinations of genes from different individuals) and mutation (occasional random changes in the genes of the individuals) allow the population to remain diverse and are especially important if the problem constraints and/or requirements change over time, selection controls the diversity of the population to such a degree as to ensure the inclusion of a critical mass of fit individuals in the evolving population. The repeated application of the three GA operators causes a gradual change in the make-up of the population by the inclusion of more individuals of higher fitness, while also allowing the repeated adaptation and convergence to a new solution under changing conditions (e.g. constraints) of the problem, thus eventually producing a (near-)optimal solution to the current conditions of the problem-at-hand.

As GAs tend not to be able to consistently scale up to problems of increasing complexity or of a decision-making nature, GA-variant evolutionary (computation) algorithms (EC, EAs or ECAs) have been - and continue to be - developed (e.g. Fogel, 1995; Chiong et al., 2012).

3. THE CI PARADIGM APPLIED TO N(P)PS – AN INVESTIGATION PER N(P)P KEY-ISSUE

The CI-related research performed (and reported in the relevant literature) during the period 1990-2015 on the aforementioned N(P)P key-issues is critically discussed independently for each exponent of the CI paradigm collectively over all key-issues, and independently for each key-issue, in both cases reported both separately per publication medium and collectively over all publication media. For conciseness and homogeneity in terms of numbers of publications and NE areas covered by the five journals considered here, the publications appearing in the three ANS journals are collectively referred to as ANS.

3.1 Publication Profile - Coverage per CI Paradigm

3.1.1. ANNs

As depicted in Figure 1, the research output concerning the use of ANNs is – in general – evenly distributed over the period 1990-2015 for each of the three journals. No ANN publications appear in ANE in 1990, 1992-1993, 1999 and 2004 (a total of five years), suggesting the rather timid inauguration of non-purely signal processing techniques in NE, especially until the mid-1990s, yet the steadily increasing use of ANNs in NE from then on. PNE follows a similar – yet more intermittent[7] - path. As far as ANS publications are concerned, ANN-related research activity appears earlier than for either ANE or PNE, yet with no publications in 1990 and then again in 2000, 2005-2006, 2008, 2011-2012 and 2014 (8 years). The majority of ANN-related research appears in ANE (52%), with ANS and PNE covering 36% and only 12% of the total research output, respectively. There seems to be a rather significant gap between the publication media at hand concerning the percentage coverage of the aforementioned paradigm, with ANE being the most suitable medium for the publication of ANN-related research and tool development. It is also noted that, although the research interest in ANNs appears quite prominent in the eve of the new millennium, some time-gaps occur which it is not straightforward to explain, especially given the potential of ANNs to implement effective performance for – practically - all N(P)P operation key-issues. Overall, the applicability of ANNs is boosted by their formal, mathematical-based justification of convergence and stability underlying their construction, as well as by their clear and explicit architecture, i.e. features that facilitate the deployment of this paradigm in a rather straightforward and adequate manner.

3.1.2. FL

FL-related research publications are - in general – intermittent over the period 1990-2015, both when considered independently per journal and over the three journals (Figure 2). The journals peak at different times (18% in 2013, 38% in 2005 and 15% in 1994 for ANE, PNE and ANS, respectively) and do not share their periods of no-FL-related research output (1990-1993, 1997-2002, 2004, 2006-2008, 2011-2012 for ANE, 16 years overall; 1990-2000, 2002, 2006-2008, 2011 and 2013-2014 for PNE, 18 years overall; 1991-1993, 1995, 2001-2003, 2005, 2009 and 2013 for ANS amounting to 10 years overall). The majority of FL-related research results are found in ANS (46%), with 30% and 24% of publications appearing in PNE and ANE, respectively.

It is evident that the FL paradigm does not have the same diffusion as ANNs concerning the N(P)P key-issue; this is due to the fact that the application of the FL-based paradigm for appropriately formulating (i.e. representing) the problem to be solved relies heavily on the expertise of the programmer/engineer in assembling a correct, complete and well-coordinated set of fuzzy rules. The FL-based system is strongly application-dependent and – even then – remains problem-instance-specific, with the characteristic (in FL) (a) trial-and-error-based selection of fuzzy variable membership functions and (b) linguistic expressions for binding together the fuzzy rules, often lacking a sound theoretical basis. As a result, considerable effort may be needed for establishing the optimal shapes of the membership functions as well as the appropriate number, shapes and limits of the created fuzzy

Figure 1a. Yearly percentage (% over the period 1990-2015) of purely ANN-related publications from ANE

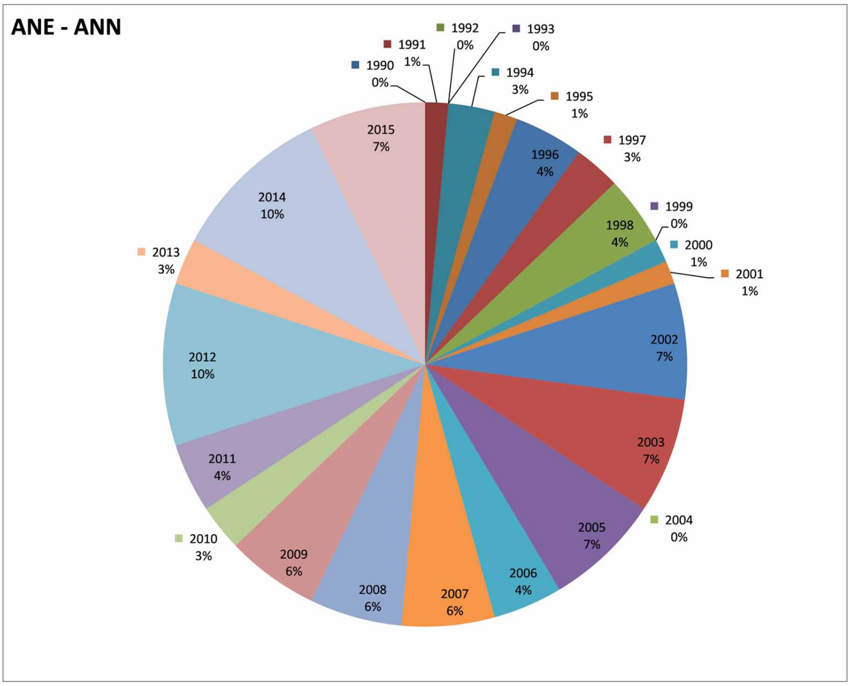


Figure 1b. Yearly percentage (% over the period 1990-2015) of purely ANN-related publications from PNE

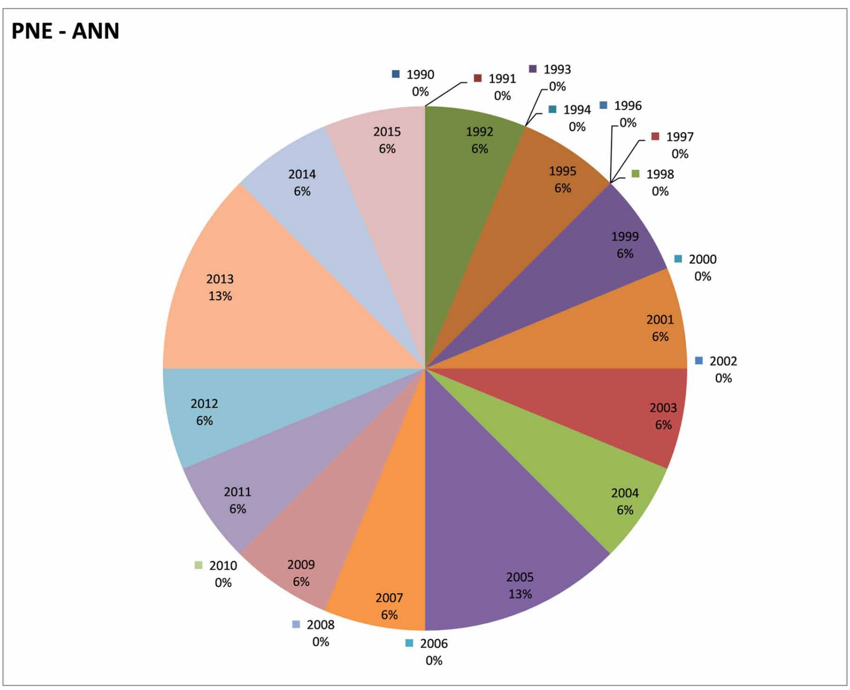


Figure 1c. Yearly percentage (% over the period 1990-2015) of purely ANN-related publications from ANS

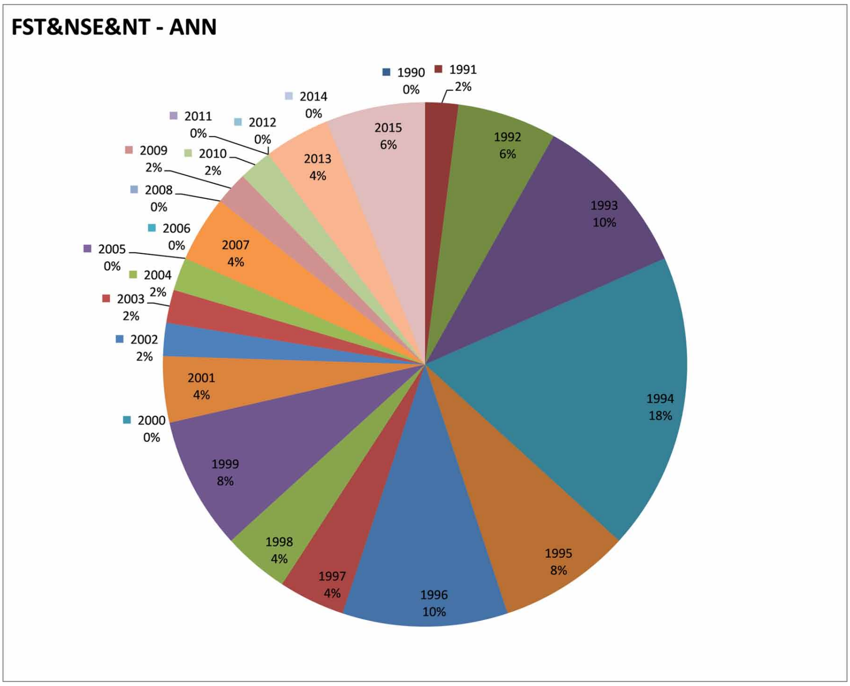


Figure 1d. All journals ANN

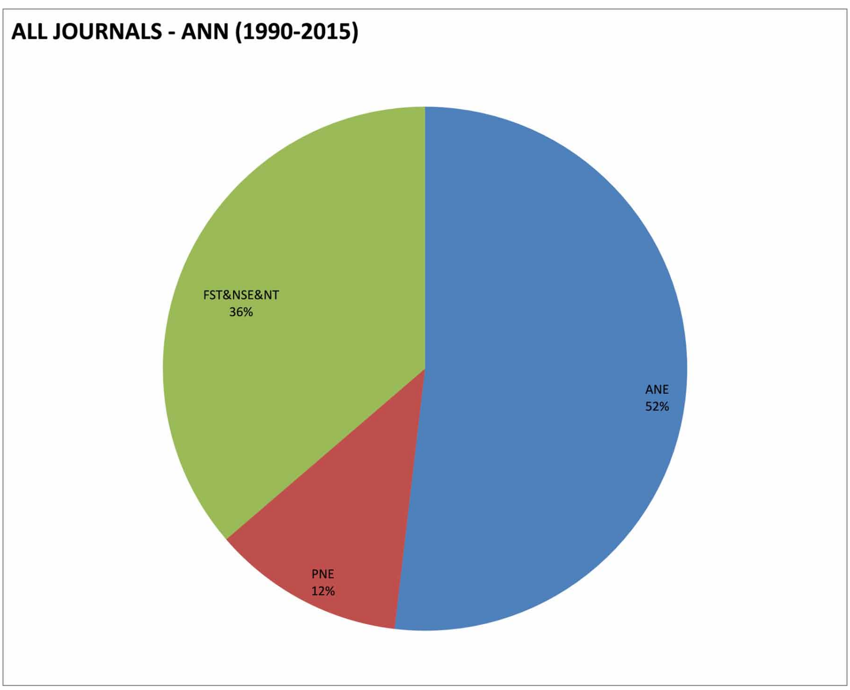


Figure 2a. Yearly percentage (% over the period 1990-2015) of purely FL-related publications from ANE

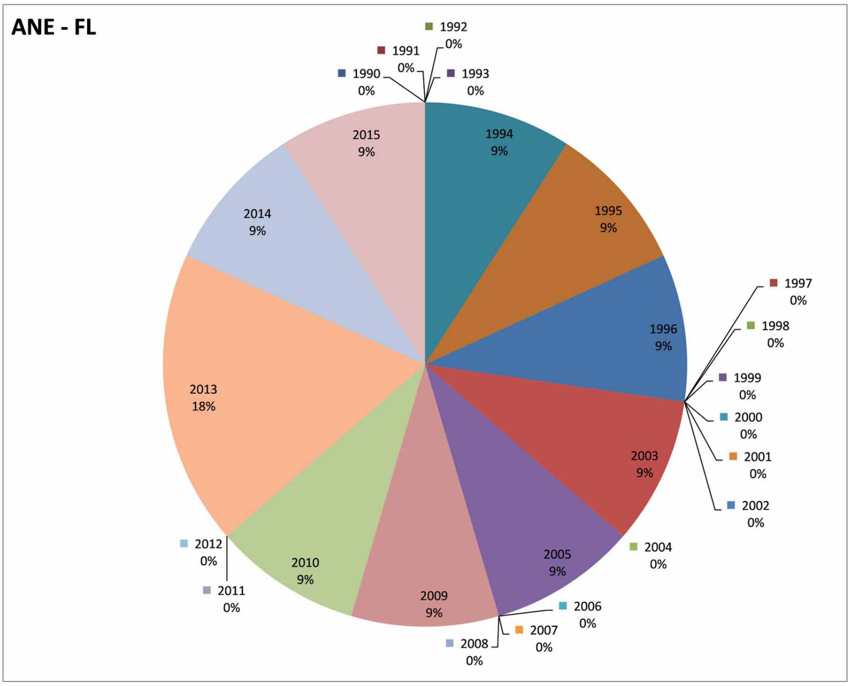


Figure 2b. Yearly percentage (% over the period 1990-2015) of purely FL-related publications from PNE

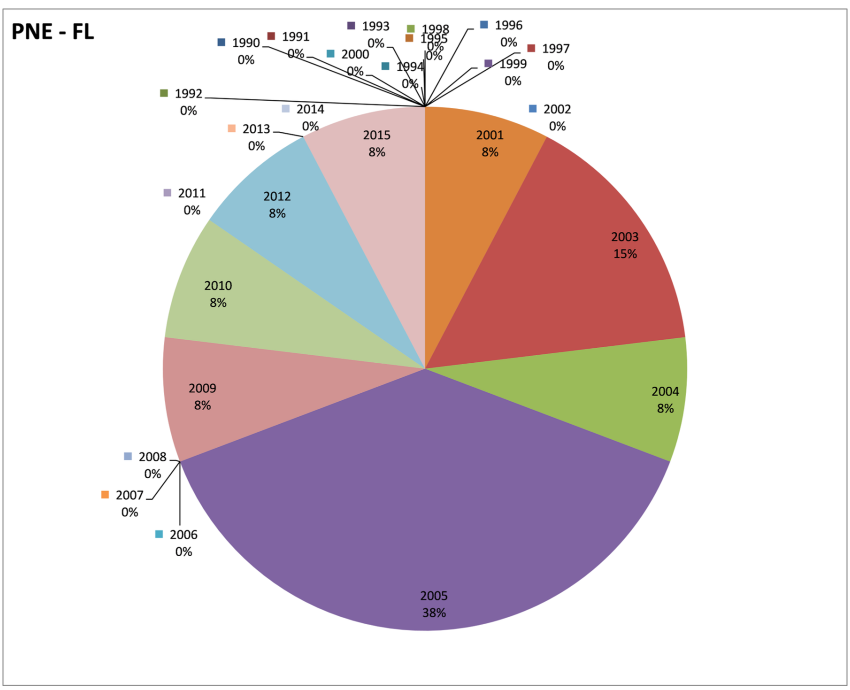


Figure 2c. Yearly percentage (% over the period 1990-2015) of purely FL-related publications from ANS

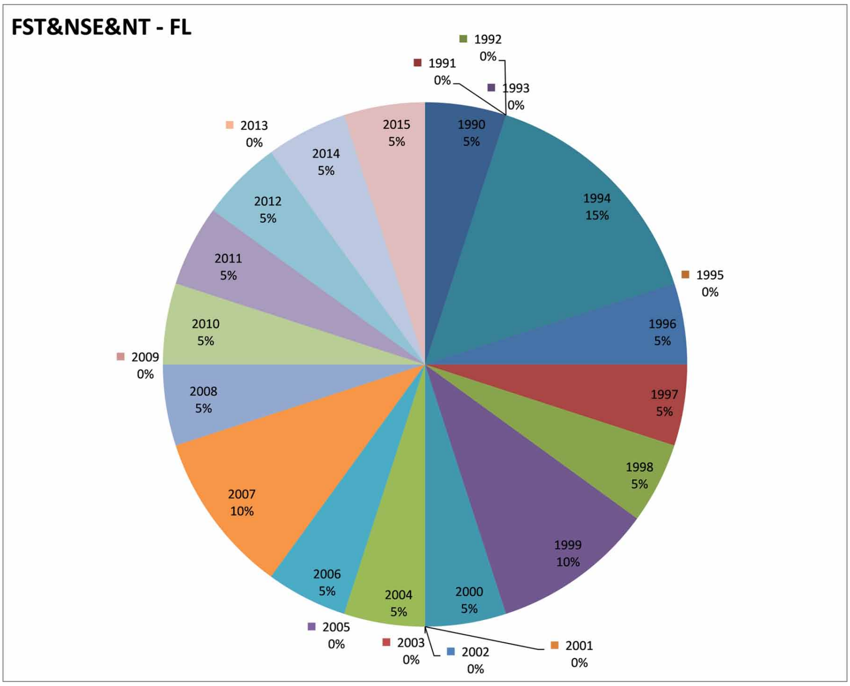
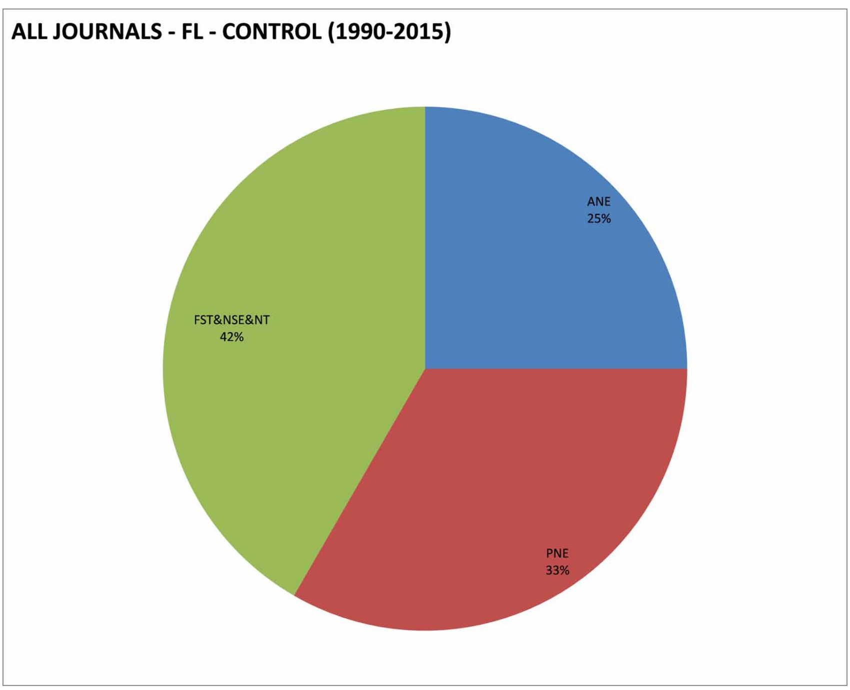


Figure 2d. All journals: FL control



rules. The observed lower diffusion of the FL paradigm is shared across all publication media, with significant time-gaps of FL-related published research overall, and ANE being the least preferred medium of publication of the FL-based implementations and tools. PNE demonstrates the largest time gaps of FL-related publications (as also observed for ANNs). The ANS publications lie somewhere in-between with a more balanced representation of FL-based implementations.

3.1.3. GAs

Illustrated in Figure 3, ANS constitutes the major medium of publishing GA-related research (50% of the relevant literature), followed by PNE and ANE (31% and 19%, respectively). The three journals demonstrate a temporal difference in GA-related publication activity, (A) totaling 12, nine and three years of GA-related publications, respectively (namely 1995-1998, 2001-2002, 2006, 2008-2011, 2014 for ANS; 2003, 2005, 2008 and 2010-2015 for PNE; and 2006, 2013 and 2014 for ANE), (B) with publication peaking in 2006 for ANS, 2011 for PNE and 2013 for ANE, with 19, 20 and 50% of the total publications, respectively. GAs have been mostly implemented from 2000 onwards, with only sporadic research published in the second half of the 1990s in the ANS journals. The rather small diffusion of this technique can be attributed to the fact that GAs have to be specifically formulated in order to efficiently address problems relating to N(P)P key-issues.

Still, the research interest in the GA paradigm has grown in the last 15-20 years; it appears that the increasing availability of computational resources (such as process power, memory) has afforded the necessary resources to this more computationally demanding paradigm for the generation of optimal solutions within more viable execution-times. Especially for on-line and real-time applications, the aspect of execution time has to be taken into account since CI-tools in general (and on-line operating GAs, more specifically) are dependent on an appropriate representation of the optimization problem for delivering timely/efficient and consistently (near-)optimal solutions. As also observed in FL, reliably near-optimal and – at the same time - efficient solutions require an in-depth understanding (and appropriate representation/codification) of the problem to be solved.

3.2. Publication Profiles - Coverage per Key-Issue

3.2.1 Control

As shown in Figure 4, the research output concerning N(P)P control issues makes its appearance - and also ceases to be used - earliest in ANS for all three exponents of the CI paradigm. ANE constitutes the preferred journal for ANN-related research in control, with both PNE and ANS being chosen for FL-based implementations and applications; still, PNE remains - by far - the preferred means of publication for GA-based solutions to N(P)P control issues. It can also be deduced from Table 1 that ANN-based tools outnumber both FL- and GA-based applications, thus revealing a preference for this technique as far as control problems are concerned. The most implemented ANN-based architecture is BP (14 out of 26 research outputs, Table 1(a)), followed by combinations of BP with other architectures and CI methodologies. It is worth noting that simulated data have been utilized in 22 out of 26 ANN research outputs. The same applies to all (12, Table 1(b)) FL and to the majority (5 out of 8, Table 1(c)) of GA implementations. Clearly, significantly more research effort must be invested to real data for validating the effectiveness of (and, thus, further boosting confidence in) the non-parametric CI paradigm.

As far as ANNs are concerned, the main focus of published research has been primarily on power (level) control, followed by reactivity compensation and load-following operations. A plethora of input information is utilised for attaining a satisfactory level of performance, such as thermo-hydraulic (e.g. temperature, pressure, mass flow of several critical components) and neutron-derived parameters (e.g. neutron flux and diffusion). There seems to be no apparent relationship between the nature of the provided information/data and the ANN architecture employed, whereby no insight can be derived as to what kind of information/parameters/measurements are best suited to each application, or which CI paradigm (and particular methodology) is better-suited to the application/

Figure 3a. Yearly percentage (% over the period 1990-2015) of purely GA-related publications from ANE

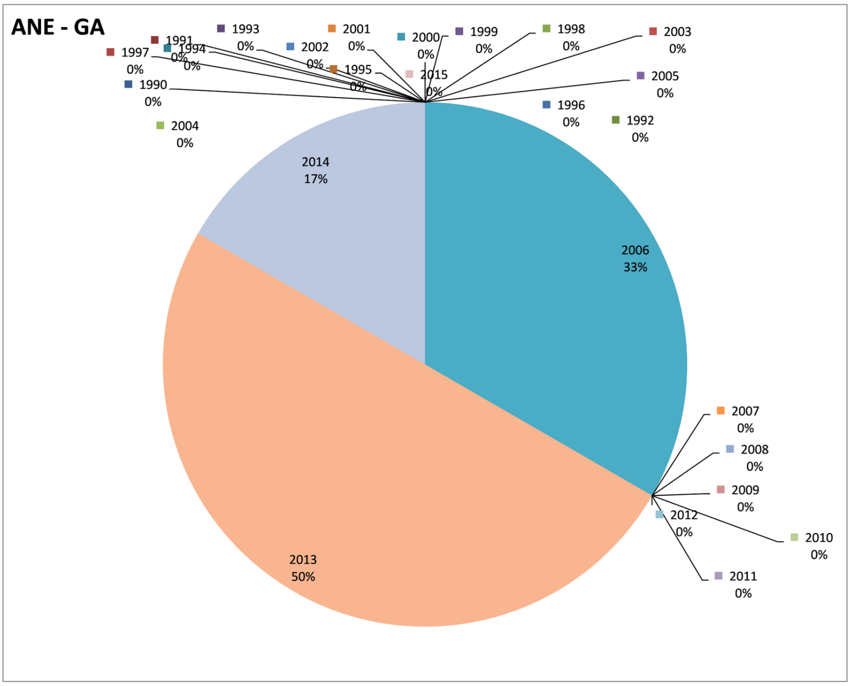


Figure 3b. Yearly percentage (% over the period 1990-2015) of purely GA-related publications from PNE

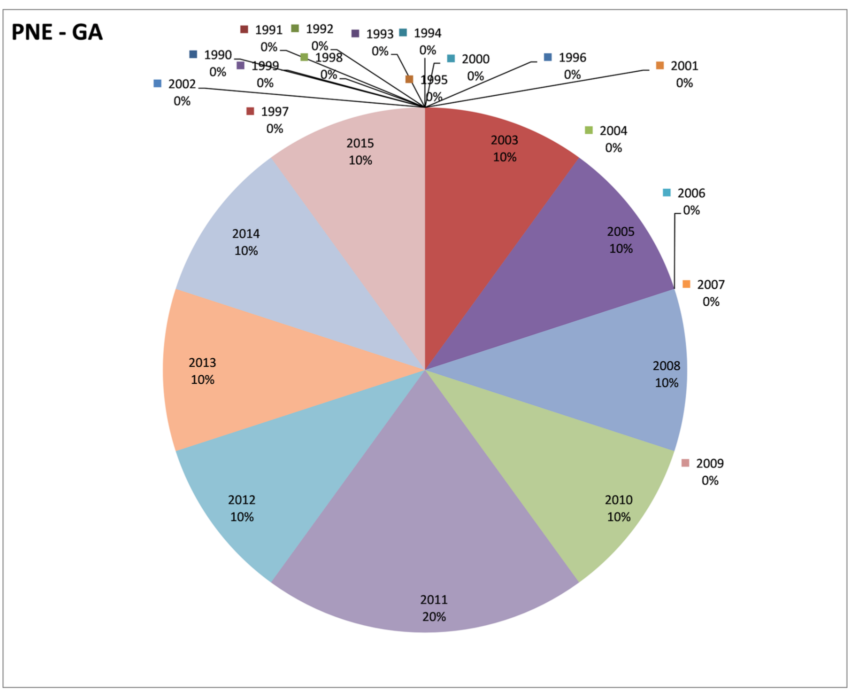


Figure 3c. Yearly percentage (% over the period 1990-2015) of purely GA-related publications from ANS

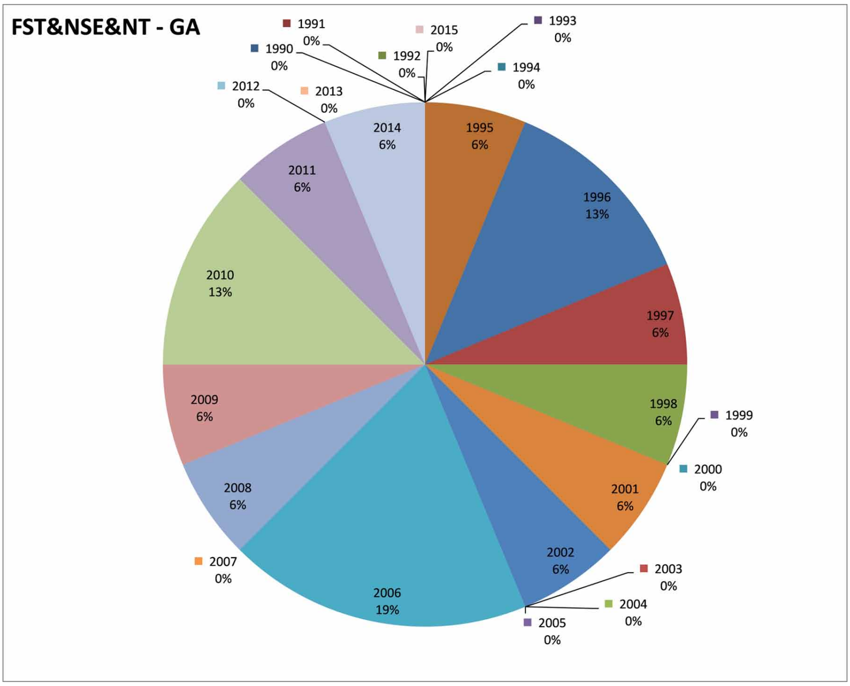


Figure 3d. All journals: GA

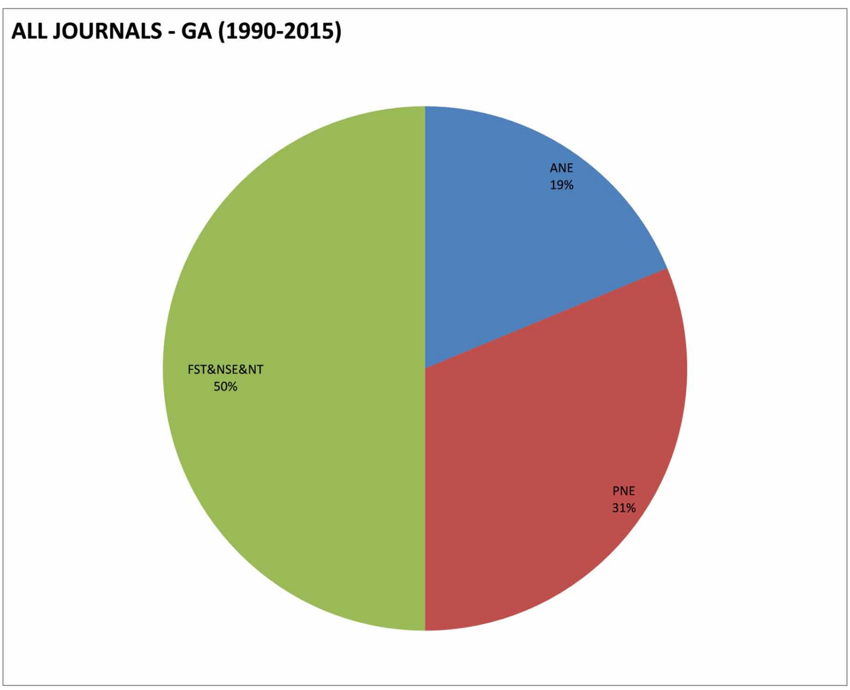


Table 1. Key-issue: Control; CI paradigm: ANNs (a), FL (b), GAs (c) combinations (d)

journal	year	type of ANN	Authors	Data	Reactor
(a)					
NT	1992	BP & SOM	Guo and Uhrig, 1992	Real	N.A.S.
NT	1995	GFNN	Park and Cho, 1995	Simulated	N.A.S.
FST	1996	4L	Albanese et al., 1996	Simulated	ITER
ANE	1998	BP	Dubey et al., 1998	Simulated	PHWR
ANE	1998	BP	Dubey et al., 1998	Simulated	AHWR
NT	1998	BP	Garis et al., 1998	Simulated	PWR
NSE	1999	BP	Accorsi et al., 1999	Simulated	PWR
NSE	1999	BP & GPT	Lysenko et al., 1999	Simulated	PWR
NT	1999	BP	Seong et al., 1999	Simulated	PWR
NT	2001	LOGFNN	Uluyol et al., 2001	Simulated	PWR
ANE	2002	BP	Akkurt and Colak, 2002	Simulated	PWR
NSE	2002	BP	Seong et al., 2002	Simulated	PWR
ANE	2003	RNN	Boroushaki et al., 2003	Simulated	VVER 320
PNE	2004	BP	Mazrou and Hamadouche, 2004	Real	LWR
ANE	2005	BP	Arab-Alibeik and Setayeshi, 2005	Simulated	PWR
ANE	2005	RNN	Boroushaki et al., 2005	Simulated	VVER 320
ANE	2006	BP	Souza and Moreira, 2006	Real	LWR
NSE	2007	CNN	Boroushaki et al., 2007	Simulated	5 MW thermal pool-type cubic research reactor core
ANE	2007	MLP	Jang et al., 2007	Simulated	Soluble boron-free
FST	2007	RBNN	Vitela, 2007	Simulated	D-T fueled tokamak
ANE	2011	BP	Lin and Chang, 2011	Simulated	PWR - KSNPs
ANE	2014	B-spline kernel NN	Abharian and Fadaei, 2014	Simulated	TRR
ANE	2014	BP	Bayram et al., 2014	Simulated	N.A.S.
ANE	2014	MFLNN	Coban, 2014	Simulated	LWR
ANE	2014	BP	Sarkar et al., 2014	Real	PHWR
ANE	2015	BP	Marklund and Michel, 2015	Simulated	PFR
(b)					
NT	1994	FLC	Hah and Lee, 1994	Simulated	PWR
NT	1997	FLC	Lin et al., 1997	Simulated	ABWR
NT	1998	FLC	Lin and Yang, 1998	Simulated	ABWR
NT	1999	FLC	Kavaklioglu and Upadhyaya, 1999	Simulated	PWR & BWR
ANE	2003	FLC	Marseguerra and Zio, 2003	Simulated	PWR
PNE	2004	Fuzzy Rule-Based System	Guimaraes and Lapa, 2004	Simulated	PWR
NSE	2004	FLC	Liu et al. 2004	Simulated	PWR
PNE	2005	FL	Adda et al., 2005	Simulated	Research reactor
PNE	2005	FLC	Benitez-Read et al., 2005	Simulated	TRIGA Mark III

continued on following page

Table 1. Continued

journal	year	type of ANN	Authors	Data	Reactor
PNE	2012	FLC	Alireza and Shirazi, 2012	Simulated	LWR
ANE	2013	FLC	Li and Zhao, 2013	Simulated	PWR
ANE	2013	FLC	Rojas-Ramirez et al., 2013	Simulated	TRIGA Mark III
(c)					
NSE	2001	GA	Marseguerra and Zio, 2001	Experimental	Xenon-Controlled
PNE	2003	GA	Marseguerra et al., 2003	Simulated	PWR
PNE	2005	GA	Domingos et al., 2005	Simulated	PWR
ANE	2006	GA	Lee and Lin, 2006	Simulated	BWR
PNE	2010		Michálek et al., 2010	Real	VR-1
PNE	2012	QEA	Nicalau et al., 2012	Real	PWR
ANE	2013	GA	Karahroudi et al., 2013	Simulated	VVER-1000
PNE	2013	IAGA & LQG & PID	Li and Zhao, 2013	Simulated	PWR
(d)					
NT	2000	ANFIS	Lin and Shen, 2000	Simulated	PWR
ANE	2005	ANN&FL	Zhao et al., 2005	Simulated	PWR
NSE	2007	FL&GA	Marseguerra et al., 2007	Simulated	PWR
ANE	2008	ANFIS	Khorramabadi et al., 2008	Simulated	PWR
PNE	2010	ANN&GA	Coban, 2010	Simulated	TRIGA Mark II
ANE	2011	ANFIS	Lali and Setayeshi, 2011	Simulated	N.A.S.
PNE	2013	ANN&FL&GA	Oliveira and Almeida, 2013	Simulated	PWR

data at hand; this may also explain why considering the research outputs in chronological order does not reveal any particular temporal trend in dominant ANN architectures. It is also worth noting that the adoption of specific ANN architectures and training algorithms (e.g. FFNs trained with BP, or its variants) dovetails their application to other scientific areas. As expected, the quality of the data used in the implementations plays a pivotal role to the level of performance attained by the various ANN-based systems.

Similar remarks apply to the reported FL and GA applications, with the main goal of control remaining the consistent attainment of the desired (safe yet efficient) power level, coupled with control of the feed-water level and rod positions. Again, there is no evidence of any FL- or GA-based technique being better suited to a particular kind of data, with the data "quality" and completeness requirement (in terms of signal as well as relevant parameters) holding strong.

Finally, the published combinations (Table 1(d)) of the aforementioned CI paradigms (i) strive to tackle the inherent drawbacks and weaknesses of the constituent methodologies, while (ii) fully exploiting the advantages of each method, with the resulting combinations revealing promising results.

3.2.2. Diagnostics and Fault Detection

ANE constitutes the preferred medium of CI-oriented research for diagnostics and fault detection, followed by ANS. ANNs constitute the prevalent CI paradigm for this key-issue (27 research outputs, Table 2(a)), with FL being used less often (12 research outputs, Table 2(b)). The total absence of

Figure 4a. Yearly percentage (% over the period 1990-2015) of purely control-focused publications using the ANN exponent

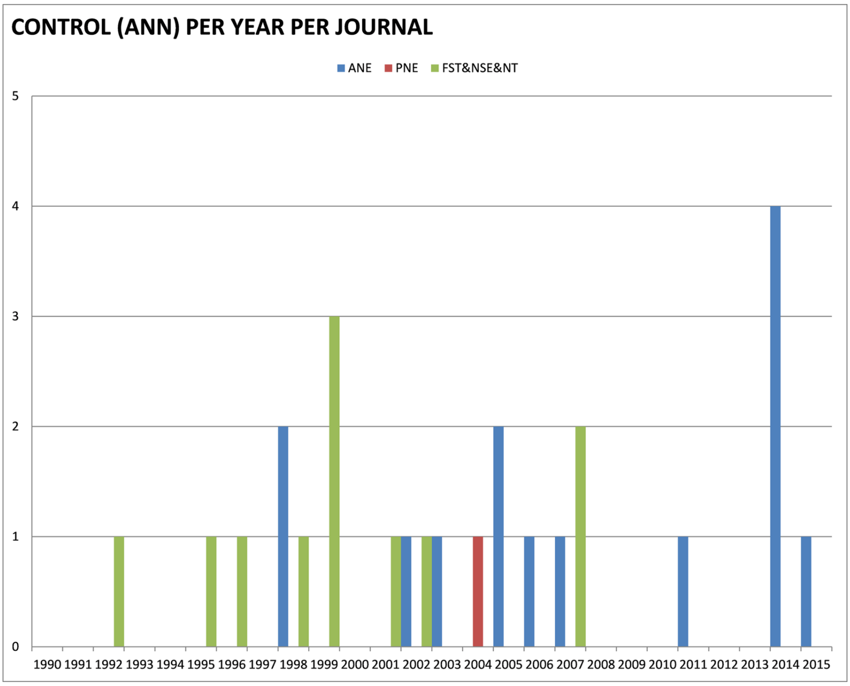


Figure 4b. Yearly percentage (% over the period 1990-2015) of purely control-focused publications using the ANN exponent

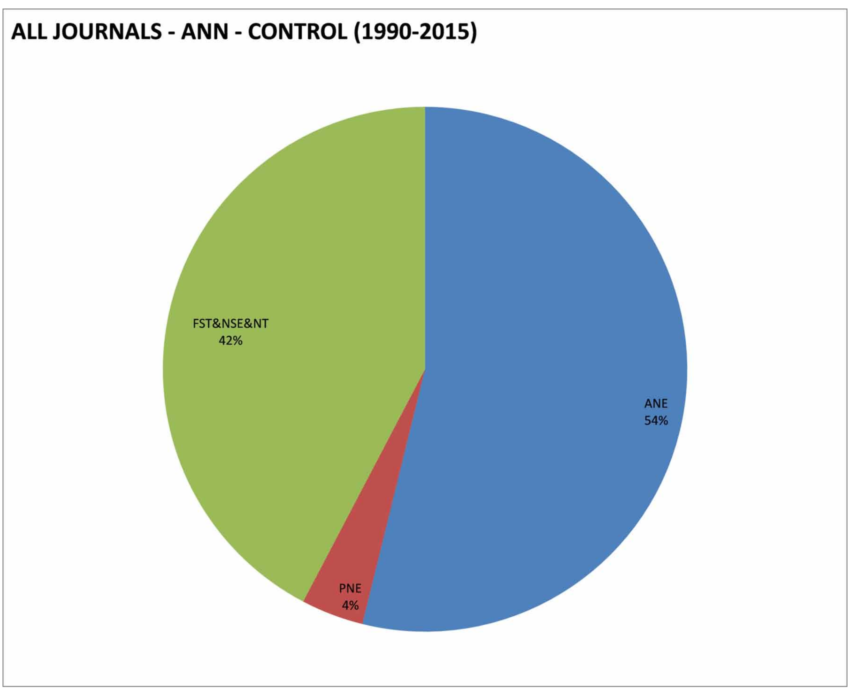


Figure 4c. Yearly percentage (% over the period 1990-2015) of purely control-focused publications using the FL exponent

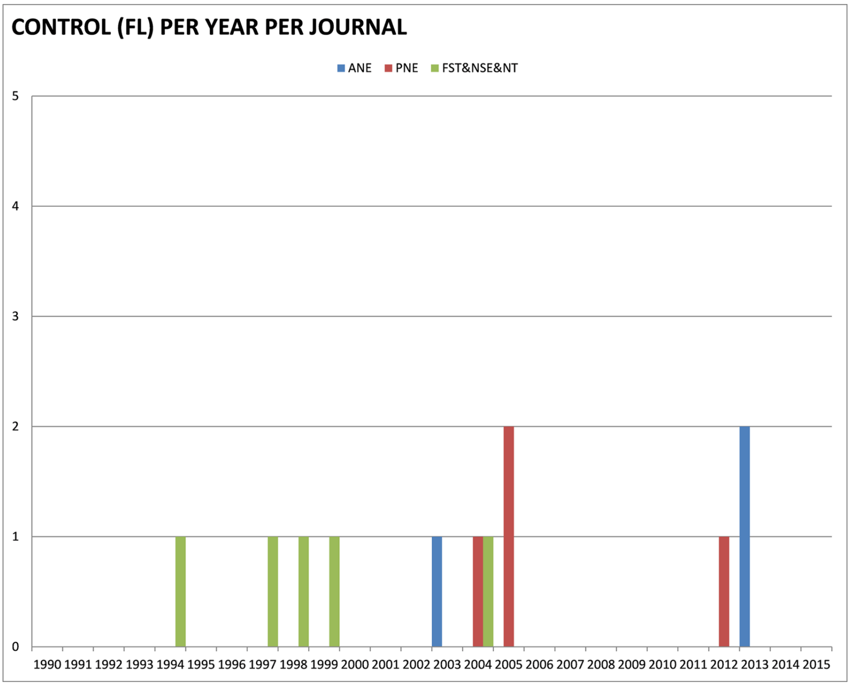


Figure 4d. Yearly percentage (% over the period 1990-2015) of purely control-focused publications using the FL exponent

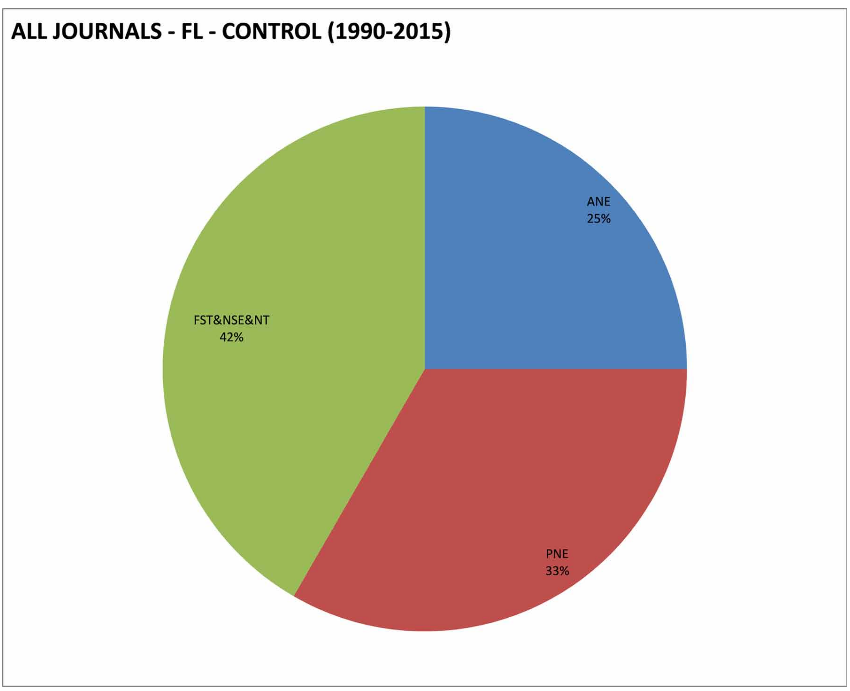


Figure 4e. Yearly percentage (% over the period 1990-2015) of purely control-focused publications using the GA exponent

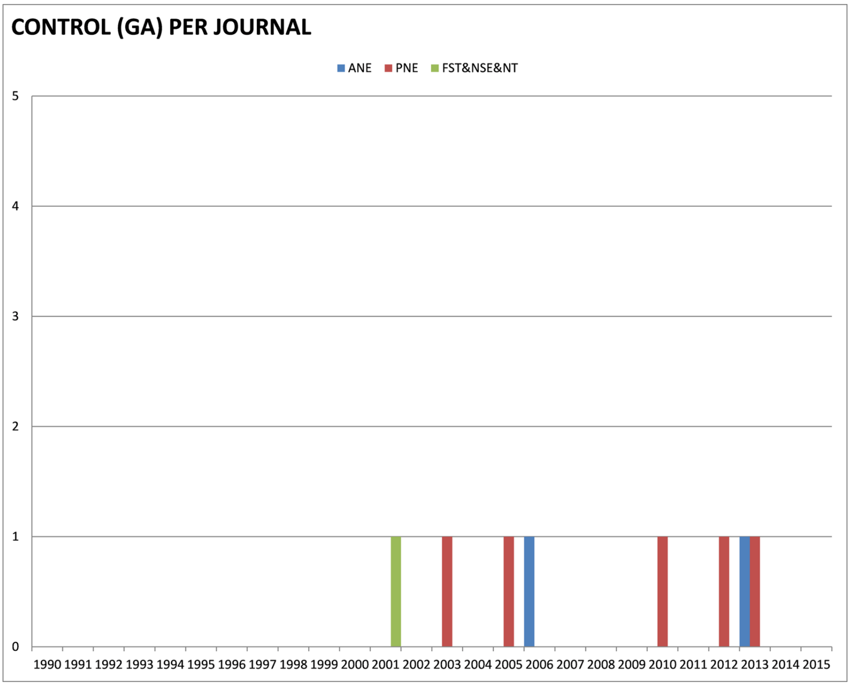
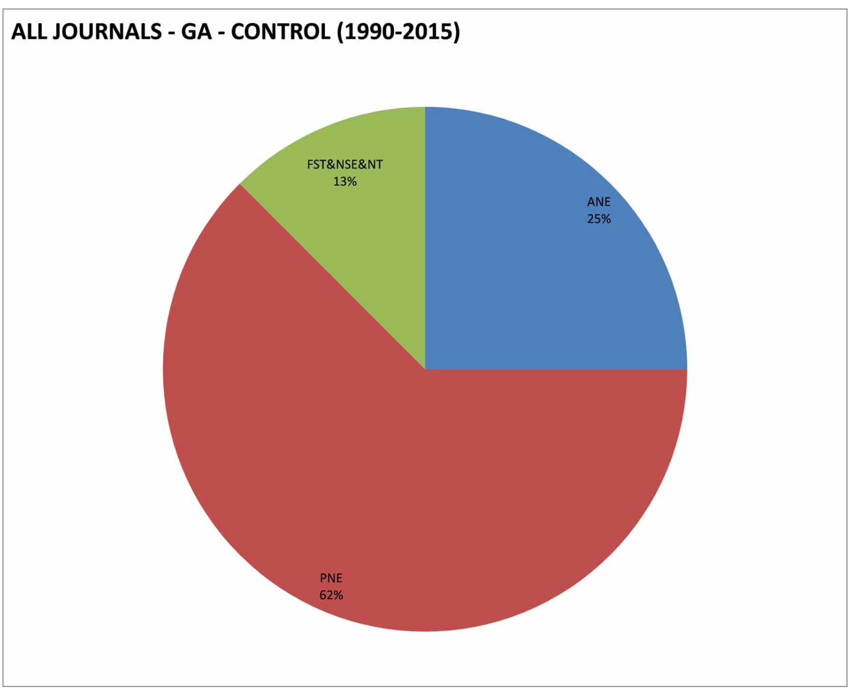


Figure 4f. Yearly percentage (% over the period 1990-2015) of purely control-focused publications using the GA exponent



the GA exponent is most probably due to the relative difficulty to represent and manipulate such problems in the form of interacting genes and chromosomes. ANS constitutes the earliest medium of publication for the two CI exponents, with PNE and (especially) ANE starting off later but remaining consistent over time. Regarding the ANN architectures, 18 out of 27 research outputs are deployed with BP ANNs (including BP extensions and variants), which is most probably due to their simplicity and robustness of operation as well as their superior approximation performance and prediction accuracy. Simulated data are utilized in the majority of control-oriented research (Table 2(a-b)), with 18 and nine (out of a total of 27 and 12, respectively) ANN and nine FL-based publications. The Diagnostics and Fault Detection (D-FD) key-issue is closely related to that of Control, which can be explained by the focus of both key-issues on the assessment of N(P)P operation per se and/or its critical components. Especially concerning ANNs, there is no apparent trend in the (preferred) choice of ANN architecture over time. The same is true of the FL paradigm as well as their combinations (Table 2(c)), the only exception being – perhaps - a preference for FL-based problem formulations as far as sensor validation applications are concerned.

3.2.3. Monitoring

ANNs constitute the prevalent tool for providing viable solutions to the monitoring key-issue (49 research outputs, Table 3(a)), with their application persisting throughout the entire 1990-2015 period. Research results for the other two CI exponents appear significantly later (1996 and 2006, respectively), with implementations remaining quite limited (seven FL-related research outputs against two FL-GA-combinations and only two GA implementations), as shown inTable 3(b-c)), especially for GAs. Derived from Table 3(a), the BP architecture and its variants remain the most preferable (28 out of a total of 49 research outputs). Different architectures, like RBF networks, have also been deployed, primarily for tackling problems expressed as classification tasks. The same applies to FL, with monitoring handled as a classification problem. Again, the utilization of simulated data instead of real measurements is prevalent, (amounting to 39 out of 49, and 5 out of 7, outputs in ANNs and FL, respectively (Table 3(a),(b)), a finding that is “reversed” in CI combinations where real data is used (in 6 out of 9 outputs, Table 3(d)). The most prevalent approach for CI combinations is based on ANN-based fuzzy inference systems (ANFIS), with only two pieces of research utilizing GAs coupled with ANNs.

As observed for the Control and Diagnostics key-issues, the data used pertain to thermo-hydraulic parameters (temperature, pressure, mass flow), neutron flux, neutron noise etc.; this is not surprising, since both key-issues are closely related to monitoring. It is also observed, primarily in the most recent years, that a considerable amount of Cellular and RBF neural networks are utilized on neutron-type measurements. Although interesting, a formal theoretical investigation as well as a justification of the appropriateness/suitability of such a type of data for/to these ANN architectures needs to be performed.

3.2.4. N(P)P Operations

ANNs and GAs are preferred over the FL exponent (25 research outputs for ANNs, 21 research outputs for GAs and only 8 for FL, Table 4(a-c)), with ANN-related research publications occurring mostly in ANE and the other two CI exponents appearing mostly in ANS, which also hosts the earliest relevant literature for all exponents. As seen in Table 4(a), 14 out of 25 ANN-derived research outputs are based on the BP architecture and its variants. The most interesting fact regarding the N(P)P Operations key-issue is the extensive use of GA methods, especially when compared to the Control, Diagnostics and Monitoring key-issues (as shown above), a finding that is due to the fact that the structure and formulation underlying GAs is more appropriate for this type of problems. Although, once more, the prevalence of simulated data is evident, the types of utilized data are more diverse for this key-issue, since they are highly case-study dependent.

Table 2. Key-issue: Diagnostics & Fault Detection; CI paradigm: ANNs (a), FL (b), combinations (c)

journal	year	Type of ANN	Authors	Data	Reactor
(a)					
NT	1991	BP	Roh et al., 1991	Simulated	PWR
PNE	1992	BP	Marseguerra et al., 1992	Simulated	N.A.S.
NT	1992	RMLP	Parlos et al., 1992	Simulated	N.A.S.
NSE	1994	DNANN	Basu and Bartlett, 1994	Simulated	BWR
NT	1994	BP	Kim and Bartlett, 1994	Simulated	PWR
ANE	1994	BP	Marseguerra and Zio, 1994	Simulated	N.A.S.
NSE	1994	Boltzmann machine	Marseguerra and Zio, 1994	Simulated	N.A.S.
NT	1994	ABP	Parlos et al., 1994	Simulated	N.A.S.
ANE	1994	Perception-based	Racz and Kiss, 1994	Real	VVER 1000
NT	1995	PNN	Tal et al., 1995	Simulated	PWR
ANE	1996	BP	Fantoni and Mazzola, 1996	Simulated	BWR
NT	1996	MLPBP	Fantoni and Mazzola, 1996	Simulated	BWR
NSE	1996	MLPBP	Marseguerra et al., 1996	Real	PWR
NSE	1996	FFNN	Pazsit et al., 1996	Real	PWR
ANE	1996	MLP	Yan and Upadhyaya, 1996	Real	ORNL
PNE	2001	BP & Other	Keyvan, 2001	Real	EBR-II
ANE	2005	BP	Kim et al., 2005	Real	N.A.S.
PNE	2005	MLP	Lee and and Seong, 2005	Simulated	N.A.S.
ANE	2005	AANN	Marseguerra and Zoia, 2005	Experimental	N.A.S.
ANE	2005	AANN	Marseguerra and Zoia, 2005	Simulated	BWR
ANE	2006	AANN	Marseguerra and Zoia, 2006	Simulated	BWR
ANE	2010	Bootstrapped ANN	Zio et al., 2010	Simulated	GFR
PNE	2011	MLP & RBP & WT	Hadad et al., 2011	Real	VVER 1000
ANE	2012	MLP	Elnokity et al., 2012	Simulated	ETRR-2
PNE	2013	BP	Dzwinel et al., 2013	Simulated	IBR-2
ANE	2013	ANN-PSVR	Liu et al., 2013	Real	N.A.S.
PNE	2014	BP	Hosseini and Vosoughi, 2014	Simulated	VVER 1000
(b)					
NT	1990	FL & PDM	Holbert and Upadhyaya, 1990	Real	PWR & EBR-II
NSE	1994	FL	Holbert et al., 1994	Simulated	N.A.S.
ANE	1994	Fuzzy Signed Disgraph Method	Park and Seong, 1994	Real	Kori-2 NPP
ANE	1996	Fuzzy Logic	Heger et al., 1996	Simulated	N.A.S.
NT	1999	FLC	Mironidis et al., 1999	Simulated	PWR
PNE	2003	Fuzzy Logic	Kinelev et al., 2003	Simulated	VVER-1000
PNE	2005	Fuzzy Logic	Garcia et al., 2005	Simulated	PWR
NSE	2006	FLC	Marseguerra et al., 2006	Real	CANDU 6
ANE	2009	Fuzzy decision tree	Zio et al., 2009	Simulated	PWR

continued on following page

Table 2. Continued

journal	year	Type of ANN	Authors	Data	Reactor
ANE	2010	Fuzzy Logic	Zio et al., 2010	Simulated	N.A.S.
ANE	2014	Fuzzy Logic	Purba, 2014	Simulated	N.A.S.
ANE	2015	Fuzzy decision tree	Purba et al., 2015	Simulated?	N.A.S.
(c)					
NT	1996	Other	Hines et al., 1996	Real	PWR
NT	1997	ANN&FL	Erbay and Upadhyaya, 1997	Real	PWR
NT	1997	ANFIS	Hines et al., 1997	Real	N.A.S.
PNE	2003	ANN&FL	Liu et al., 2003	Simulated	N.A.S.
PNE	2003	ANFIS	Upadhyaya et al., 2003	Simulated	PWR
ANE	2007	ANFIS	Guimaraes and Lapa, 2007	Simulated	LWR
PNE	2014	ANFIS	Liu et al., 2014	Simulated	N.A.S.

Table 3. Key-issue: Monitoring; CI paradigm: ANNs (a), FL (b), GAs (c) combinations (d).

journal	year	type of ANN	Authors	Data	Reactor
(a)					
ANE	1991	BP	Kostic, 1991	Experimental	PWR
NT	1993	BP	Cheon and Chang, 1993	Simulated	BWR
NSE	1993	BP	Kim et al., 1993	Simulated	PWR
NT	1993	BP	Kim et al., 1993	Simulated	PWR
NSE	1994	FFNN	Arul, 1994	Simulated	FBTR
NT	1994	MLPBP	Kavaklioglu and Upadhyaya, 1994	Real	PWR
NT	1994	ANN	Thomas and Adams, 1994	Real	PWR
ANE	1995	BP	Kozma and Nabeshima, 1995	Real	HOR
PNE	1995	BP	Vallejo and Barrio, 1995	Simulated	N.A.S.
NT	1995	BP	Van Der Hagen, 1995	Simulated	BWR
FST	1996	MLPBP	Yoshino et al., 1996	Simulated	ITER
ANE	1997	RBF	Ikonomopoulos and Hagen, 1997	Simulated	PWR
ANE	1997	BP	Kim and Chang, 1997	Simulated	PWR
FST	1997	Various	Windsor et al., 1997	Simulated	COMPASS-D
ANE	1998	MLP	Ikonomopoulos and Endou, 1998	Real	FBR
NSE	1998	BP	Tambouratzis et al., 1998	Simulated	BWR
PNE	1999	MLP	Hessel et al., 1999	Simulated	VVER 400
NSE	1999	BP	Marseguerra and Mazzarella, 1999	Simulated	PWR
ANE	1999	BP	Tambouratzis and Antonopoulos-Domis	Simulated	BWR
ANE	2000	BP	Ishitani and Yamane, 2000	Simulated	N.A.S.
FST	2001	MLFFNN	Sengupta ang Ranjan, 2001	Simulated	SST-1
ANE	2002	IAC ANN	Tambouratzis and Antonopoulos-Domis, 2002a	Simulated	BWR

continued on following page

Table 3. Continued

journal	year	type of ANN	Authors	Data	Reactor
ANE	2002	BP	Tambouratzis and Antonopoulos-Domis, 2002b	Simulated	BWR
ANE	2003	RBF	Lee and Chang, 2003	Simulated	PWR
ANE	2003	MLP	Mola et al., 2003	Simulated	PWR
PNE	2003		Ruan et al., 2003	Experimental	OECD Halden Reactor
ANE	2003	BP & 2 RNN	Seker et al., 2003	Simulated	HTTR
NSE	2004	NRNN	Suteau et al., 2004	Simulated	PWR
PNE	2005	BP & WT	Figedy and Oksa, 2005	Simulated	WWER 440 / WWER 1000
ANE	2006	MLP	Jiang et al., 2006	Real	CONSORT - Research Reactor Of Imperial College
ANE	2007	RNN	Cadini et al., 2007	Simulated	simplified nuclear reactor
ANE	2007	CNN	Hadad and Pirouzmand, 2007	Simulated	SSR
PNE	2007	DynNN	Mo et al., 2007	Simulated	N.A.S.
ANE	2008	BP & SVM	Bae et al., 2008	Simulated	Yonggwa NPP Unit 3
ANE	2008	CNN	Hadad et al., 2008	Simulated	N.A.S.
ANE	2009	CNN	Boroushaki, 2009	Simulated	BWR
NT	2009	Autoadaptive	Dumonteil, 2009	Simulated	N.A.S.
ANE	2009	BP	Montes et al., 2009	Simulated	BWR
ANE	2010	GRNN	Tambouratzis and Pàzsit, 2007	Real	KURRI
ANE	2011	CNN	Pirouzmand and Hadad, 2011	Simulated	N.A.S.
ANE	2012	BP & SVM	Cai, 2012	Simulated	N.A.S.
ANE	2012	CNN	Pirouzmand and Hadad, 2012	Simulated	N.A.S.
PNE	2013	RBF	Jiang et al., 2013	Simulated	N.A.S.
NT	2013	FFNN	Sarkar et al., 2013	Real	PHWR
ANE	2014	BP	Jingjing et al., 2014	Simulated	N.A.S.
ANE	2014	RBF	Peng et al., 2014	Simulated	ACP 100
ANE	2014	RBF	Xia et al., 2014	Simulated	PWR
NT	2015	BP	Angelo, 2015	Experimental	N.A.S.
FST	2015	ANN	Carli et al., 2015	Simulated	ITER
ANE	2015	RBF	Peng et al., 2015	Simulated	ACP 100
(b)					
NT	1996	FL	Muramatsu and Ninokata, 1996	Simulated	LMFBR
PNE	2003	FIS	Marseguerra et al., 2003	Simulated	PWR
PNE	2005	Fuzzy Classifier	Zio and Baraldi, 2005	Simulated	PWR
ANE	2005	Fuzzy Classifier	Zio, E., Baraldi, P., 2005	Simulated	PWR
PNE	2009	Fuzzy Cognitive Map	Espinosa-Paredes et al., 2009	Simulated	BWR
FST	2010	FL	Murari et al., 2010	Real	N.A.S.
PNE	2015	FIS	Deol and Gabbar, 2015	Case Study	PNGS

continued on following page

Table 3. Continued

journal	year	type of ANN	Authors	Data	Reactor
(c)					
NSE	2006	MOGA	Marseguerra et al., 2006	Simulated	PWR
ANE	2013	LSSVR & PSO	Jiang and Zhao, 2013	Simulated	liquid-cooled nuclear reactors
(d)					
NT	1993	ANN&FL	Ikonomopoulos et al., 1993	Real	PWR
PNE	1995	ANFIS	Kozma et al., 1995	Real	HOR
NT	1999	ANFIS	Lin and Lin, 1999	Simulated	Taiwan Power Company Maanshan Compact Simulator
NT	1999	ANFIS	Na, 1999	Real	N.A.S.
PNE	2004	ANFIS	Marseguerra et al., 2004	Simulated	PWR
PNE	2006	ANN&GA	Mol et al., 2006	Simulated	PWR
NT	2007	ANN&GA	Lee and Lin, 2007	Real	BWR
PNE	2009	ANFIS	Oliveira and Schirru, 2009	Real	PWR
ANE	2011	ANFIS	Costa et al., 2011	Real	PWR

An increasing variety of ANN architectures, other than BP, appears in recent years (Table 4(a)), with this trend – however - not being as intense as for the monitoring key-issue. Other than fuel management as well as loading and reactor design, the range of N(P)P operations tackled has expanded in time, covering aspects of operations with radiation dose absorption and variation, operation guidance systems, prediction and control of nuclear power generation, signal encryption etc.

A similar time-based pattern is evident for GA applications (Table 4(c)), with some quite innovative variants appearing in recent years. The vast majority of GA-based research has focused upon solving critical optimization issues, with only one piece of research dedicated to classification. In a similar fashion, the CI combinations (Table 4(d)) favour ANN/GA combinations over ANFIS systems, something that is unlike what has been observed for the key-issues of Control, Diagnostics and Monitoring.

3.2.5. Proliferation and Resistance Applications

Only three relevant publications appear in the 1990-2015 relevant literature, the first based on ANNs and published in ANE in 1996, with the other two employing FL and appearing in ANS in 2007 and 2012, respectively (Table 5).

3.2.6 Sensor and Component Reliability

The relevant literature is scant, represented by three quite recent relevant publications, two using ANNs and published in ANE in 2009 and 2015, and one being FL-oriented and appearing in ANS in 2014 (Table 6). It will be of interest to observe how this key-issue evolves in the future.

3.2.7. Spectroscopy

A total of five relevant publications (Table 7) appear in the relevant literature. The two publications in ANE (appearing in 2012 and 2013) are based on ANNs, with one of the remaining three publications appearing in ANS and employing GAs (2009) and two employing FL (2011 and 2015).

Table 4. Key-issue: N(P)P Operations; CI paradigm: ANNs (a), FL (b), GAs (c), combinations (d).

journal	year	type of ANN	Authors	Data	Reactor
(a)					
NT	1992	MLP & SOSLA	Bartlett and Uhrig, 1992	Simulated	N.A.S.
NSE	1993	Barto-Sutton	Jouse and Williams, 1993	Simulated	PWR
NT	1993	ANN	Ohga and Seki, 1993	Simulated	BWR
NT	1994	RMLPBP	Parlos et al., 1994	Simulated	BWR
NT	1994	MLPBP	Reifman and Vitela, 1994	Simulated	PWR
NT	1995	RNN	Wacholder et al., 1995	Simulated	N.A.S.
NT	1997	BP	Keyvan et al., 1997	Real	N.A.S.
ANE	2001	ANN-OLL	Jang et al., 2001	Simulated	PWR
ANE	2002	BP	Khajavia et al., 2002	Simulated	PWR
ANE	2002	HNNA	Sadighi et al., 2002	Simulated	PWR
ANE	2003	BP	Faria and Pereira, 2003	Simulated	PWR
NSE	2003	MLPBP	Oritz and Requena, 2003	Simulated	BWR
ANE	2007	MLP	Mo et al., 2007	Simulated	PWR
ANE	2008	MLP	Kucuk, 2008	Simulated	N.A.S.
ANE	2008	Bootstrapped ANN	Secchi et al., 2008	Simulated	RBMK-1500
PNE	2009	BP	Hedayat et al., 2009	Simulated	NRR
ANE	2011	GRNN	Mol et al., 2011	Real	Argonauta research reactor
PNE	2012	BP	Aghina et al., 2012	Simulated	PWR
ANE	2012	BP	Mirvakili et al., 2012	Simulated	VVER 1000
ANE	2012	HNNA	Pazirandeh and Tayefi, 2012	Simulated	VVER 1000
NT	2013	MINN	Vu et al., 2013	Simulated	N.A.S.
NT	2015	Levenberg-Marquardt	Chatzidakis et al., 2015	Simulated	N.A.S.
ANE	2015	MLP	Leniau et al, 2015	Simulated	PWR-MOX
ANE	2015	RNN	Ortiz-Servin et al., 2015	Simulated	BWR
PNE	2015	MLP	Thiolliere et al., 2015	Simulated	Subcrticica 1
(b)					
NT	1994	FP	Yu et al., 1994	Simulated	BWR
ANE	1995	Fuzzy TS	Park and Seong, 1995	Simulated	N.A.S.
NT	2000	FAR	Eisenhawer et al., 2000	Simulated	N.A.S.
PNE	2001	Fuzzy	Moon and Kang, 2001	Previous study (Shin et al, 1994)	N.A.S.
PNE	2005	Fuzzy Logic	Fiordaliso and Kunsch, 2005	Simulated	N.A.S.
NT	2007	FIS & Tabu	Martin Del Campo, et al., 2007	Simulated	BWR
FST	2008	FL	Anghel, 2008	Real	CANDU
PNE	2010	Fuzzy Logic	Eustaquio de Vasconcelos et al., 2010	Simulated	N.A.S.
(c)					
NT	1995	CIGARO	DeChaine and Feltus, 1995	Simulated	PWR
NSE	1996	CIGARO	DeChaine and Feltus, 1996	Simulated	PWR

continued on following page

Table 4. Continued

journal	year	type of ANN	Authors	Data	Reactor
NSE	1996	MOGA	Parks, 1996	Simulated	PWR
NT	1997	GA	Omori et al., 1997	Simulated	LWR
NT	1998	GA	Aumeier and Forsmann, 1998	Simulated	N.A.S.
NSE	2002	GA 2 stage	Kobayashi and Aiyoshi, 2012	Simulated	BWR
FST	2006	GA	An et al., 2006	Simulated	EAST
ANE	2006	NIGA	Yilmaz et al., 2006	Real	PWR
NT	2006	GA	Yilmaz et al., 2006	Simulated	PWR
NT	2008	GA	Mansilla, 2008	Simulated	VHTR
PNE	2008	NIGA	Pereira and Sacco, 2008	Simulated	PWR
NSE	2010	GA &PEBBED	Gougar et al., 2010	Simulated	RBR
FST	2010	GA	Santos and Cantos, 2010	Real	TJ-II stellarator
PNE	2011	GA	François et al., 2011	Simulated	BWR
NT	2011	GA & RANS	Lee and Kim, 2011	Simulated	PBMR
PNE	2011	Enhanced Integer Coded	Norouzi et al., 2011	Real	PWR
ANE	2013	Parallel Integer Coding	Norouzi et al., 2013	Simulated	TRR & BNPP
NSE	2014	GA&CAFCA	Passerini et al., 2014	Real	LWR
PNE	2014	DE	Sacco and Hendreson, 2014	Simulated	cylindrical 3-enrichment-zone reference reactor
ANE	2014	GA & SI/GA	Zameer et al., 2014	Real	CHASN UPP Unit 1
PNE	2015	EHS	Poursalehi, 2015	Real	KWU PWR & VVER-440
(d)					
NSE	1993	ANN&FL	Kim et al., 1993	Simulated	N.A.S.
NT	1995	Other	Chang et al., 1995	Simulated	PWR
ANE	2003	ANN&GA	Erdogan and Geckinli, 2003	Real	PWR
NSE	2004	ANN&GA	Ortiz and Requena, 2004	Real	BWR
ANE	2005	ANN&GA	Huo and Xie, 2005	Simulated	N.A.S.
ANE	2005	GA&FL	Marseguerra et al., 2005	Simulated	N.A.S.
ANE	2006	ANN&GA	Gozalvez et al., 2006	Simulated	N.A.S.
NSE	2007	ANN&GA	Ortiz et al., 2007	Real	BWR
ANE	2008	ANN&GA	Fadaei and Setayeshi, 2008	Simulated	VVER-1000
ANE	2008	ANFIS	Jeong et al., 2008	Simulated	N.A.S.
NSE	2009	ANN&FL	Ortiz et al., 2009	Simulated	BWR
ANE	2010	ANN&GA	Fadaei et al., 2010.	Simulated	IR-40
ANE	2012	ANFIS	Jeong et al., 2012	Simulated	N.A.S.
ANE	2012	ANN&GA	Khoshahval and Fadaei, 2012	Real	PWR
ANE	2014	Other	Castillo et al., 2014	Simulated	BWR
NSE	2015	Other	Burr et al., 2015	Simulated	LWR
ANE	2015	Other	Otiz-Servin et al., 2015	Simulated	BWR

Table 5. Key-issue: Proliferation & Resistance Operations; CI paradigm: ANNs (a), FL (b).

journal	year	type of ANN	Authors	Data	Reactor
(a)					
ANE	1996	BP	Antonopoulos-Domis and Tambouratzis, 1996	Simulated	N.A.S.
(b)					
FST	2007	FL	Wu et al., 2007	Experimental	N.A.S.
NT	2012	TrFNs	Otsuka, 2012	Simulated	N.A.S.

Table 6. Key-issue: Sensor and Component Reliability; CI paradigm: ANNs (a), FL (b), combinations (c).

journal	year	type of ANN	Authors	Data	Reactor
(a)					
ANE	2009	ANN-SOM	Tambouratzis and Pázsit, 2009	Real	KURRI
ANE	2015	BP	Yu et al., 2015	Simulated	AP 1000 NPP
(b)					
NT	2014	FL & DFM & ATHEANA	Pinto et al., 2014	Real	PWR
(c)					
PNE	2006	ANFIS	Guimaraes et al., 2006	Simulated	N.A.S.

Table 7. Key-issue: Spectroscopy; CI paradigm: ANNs (a), FL (b), GAs (c).

journal	year	type of ANN	Authors	Data	Reactor
(a)					
ANE	2012	BP	Medhat, 2012	Experimental	N.A.S.
ANE	2013	BP	Akkoyun, 2013	Experimental	HIFE reactions
(b)					
NT	2011	FL	Alamaniotis et al., 2011	Simulated	N.A.S.
NT	2015	FL &SVR	Alamaniotis et al., 2015	Experimental	N.A.S.
(c)					
FST	2009	GA	Yu et. Al, 2009	Simulated	Tore Supra Tokamak

3.2.8. Fusion

The relevant literature on this key-issue is scant, with only one relevant ANN-based piece of research published in ANS in 2010 (Table 8).

3.3. Combinations

The combinations of CI approaches for a number of key-issues are also (briefly) discussed in the following, as they provide some pointers as to the construction of efficient as well as accurate decision-making tools.

Table 8. Key-issue: Fusion; CI paradigm: ANNs

journal	year	type of ANN	Ref1	Data	Reactor
FST	2010	RNN	Murari et al., 2010	Simulated	N.A.S.

3.3.1. Combinations of CI Approaches Grouped by Publication Medium

A variety of combinations between the three exemplars of the CI paradigm have been successfully implemented. ANFIS and ANN-GAs constitute the prevalent CI-combinations, appearing mainly in ANE, but also in PNE and ANS (43%, 25% and 27% of the relevant literature, respectively), with FL/GA combinations being less popular. CI-combinations involving ANFIS, ANNs and FL as well as ANNs and GAs are the norm (81%, 91% and 74%, respectively), revealing complementary areas covered by each publication. Combinations of methodologies such as heuristic optimization and data mining, which appear in the ANE and ANS journals under the title "Other", do not strictly fit into the CI-paradigm; the reason they are shown here is that their occurrence (13% and 20% of the related publications, respectively) may very well point towards an evolving paradigm shift.

3.3.2. Combinations of CI Approaches per Key-Issue, Grouped per Publication Medium

An examination of the frequency of occurrence of combinations of exemplars of the CI paradigm reveals different traits for the three journals: while the N(P)P Operations key-issue ranks first in ANE and ANS (69% and 40%, respectively), monitoring is the most prevalent key-issue for PNE (37%). Both the Fault Detection & Diagnostics and the Control key-issues demonstrate the highest occurrence in the PNE journal. Finally, the ANS publications are the most consistent in terms of the overall distribution of key-issues.

4. CONCLUSION

The presented review has covered the application of CI tools (namely, artificial neural networks, fuzzy logic and genetic algorithms) to key-issues of NE and N(P)P (i.e. control, diagnostics and fault detection, monitoring, N(P)P operations, proliferation and resistance applications, sensor and component reliability, spectroscopy, fusion supporting operations), collected over the major scientific/research publication media (Annals of Nuclear Energy, Fusion Science and Technology, Nuclear Science & Engineering, Nuclear Technology, Progress in Nuclear Energy) for the period 1990-2015. Trends have been observed and uncovered overall as well as per key-issue, per journal and per CI exemplar, with the best - and some of the less successful - combinations pinpointed and critically discussed.

It is observed that CI has been gradually acknowledged as a highly promising, effective, accurate, robust tool for/approach towards safe and efficient N(P)P operation, which not only compares favourably to traditional approaches in the relevant literature, but can – furthermore - be combined with these approaches for the seamless implementation of integrated environments and tools. It seems that a closer collaboration between nuclear engineers and CI scientists/researchers would be conducive to assuring both the appropriate choice of CI methodology and its more formally correct application (in terms of representation, set-up, implementation, cross-validation). To this aim the utilisation of real cases/data would further improve the confidence in CI methods, thus facilitating the actual (on-site) deployment of the resulting tools. It would also be interesting to compare the presented findings with findings relating to the same key-issues, yet implemented using artificial as well as swarm intelligence methodologies, showing – perhaps – the advantages derived from combining all three "intelligence" paradigms, expressed via an increase in the efficiency and accuracy of attaining a solution, something that is especially important when using the uncertain, inaccurate and/or partial information available in real on-line N(P)P signals.

A future review shall demonstrate the paradigm shift that has occurred in the post-2015 era following the fruition of the bid-data paradigm and the increasingly extensive use of CI for the actual implementation of stand-alone/commercial tools based on DNNs. This may well also suggest the increasing appreciation of - and confidence in - the non-parametric nature of CI-based tools and implementations over the more traditional engineering/formal-analysis-based, parametric signal-processing methods and approaches.

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ENDNOTES

[1] The produced NE is transferred to the nuclear (power) plant N(P)P coolant in various forms, e.g. high-temperature liquid/steam in boiling water reactors (BWRs) or liquid under high-pressure in pressurised water reactors (PWRs), and subsequently converted into electricity.

[2] Pile-1 (CP-1) was the world's first nuclear reactor, built in Chicago, U.S.A. in 1942; Calder Hall was the first NPP, built in Windscale, U.K. in 1956.

[3] The optimal (shortest) trail takes on the form of a piece-wise assembly of parts of the most heavily pheromone-laid individual pheromone trails.

[4] i.e. nearest to the/a foodsource.

[5] where each variable either has or does not have the property, as given by the values of 1or 0, respectively, thus representing full membership or absolute non-membership to the property, i.e. the "true" or" false" status of a concept.

[6] with no and full membership being expressed by the values of 0 and 1, respectively. For instance, the "height" continuous variable, which takes on values within – say - [0.30 2.50]cm in crisp logic, can be represented in FL via the "very short', "short", "average", "tall", "very tall" properties/(as-a-rule overlapping) fuzzy intervals such that each value of height is represented by a certainty/belief in every property, expressed via a set of values between 0 and 1 for no- and -full-membership to each corresponding property. By appropriately representing the variables of interest, the combination of FL-based rules over a number of fuzzy variables provides the inference task with continuity, noise-resistance and robustness, while further providing the operator with a transparent as well as more easily modifiable understanding of the inference process.

[7] with no related research reported for the years 1990-1991, 1993-1994, 1996-1998, 2000, 2002, 2006, 2008 and 2010 (12 years overall)

APPENDIX A: SUPLIMENTAL FIGURES

Figure 5a. Yearly percentage (% over the period 1990-2015) of purely diagnostics and fault detection-focused publications using the ANN exponent

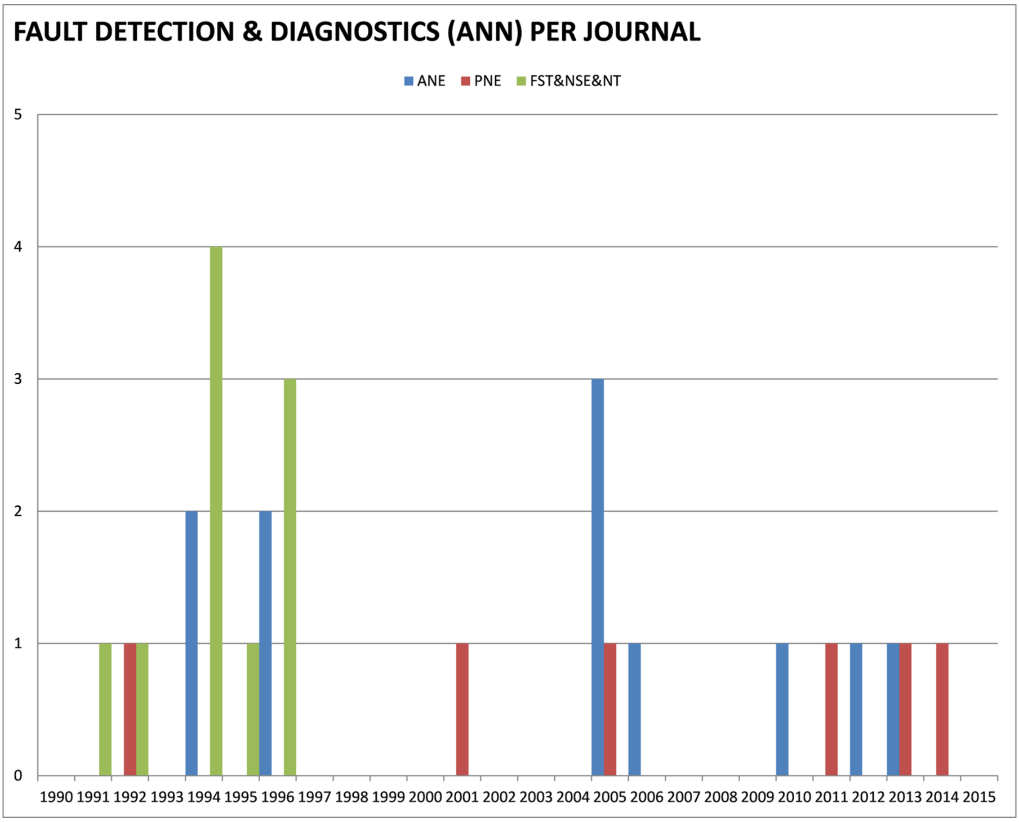


Figure 5b. Yearly percentage (% over the period 1990-2015) of purely diagnostics and fault detection-focused publications using the ANN exponent

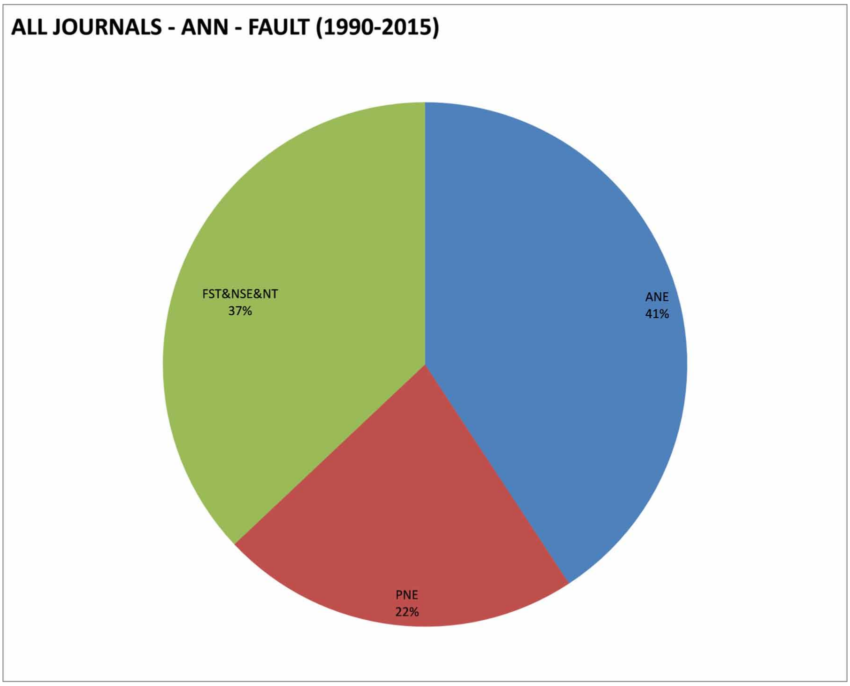


Figure 5c. Yearly percentage (% over the period 1990-2015) of purely diagnostics and fault detection-focused publications using the FL exponent

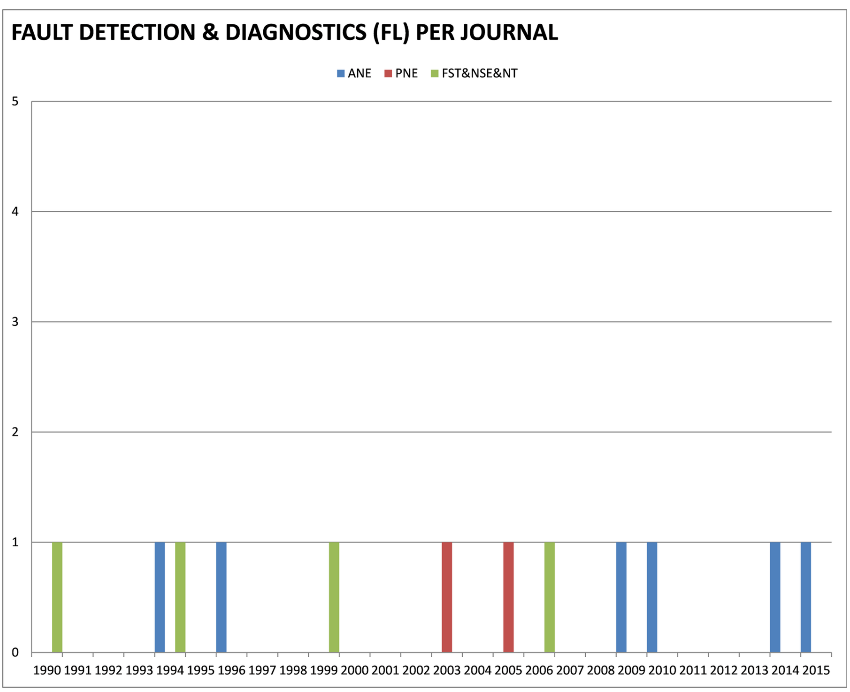


Figure 5d. Yearly percentage (% over the period 1990-2015) of purely diagnostics and fault detection-focused publications using the FL exponent

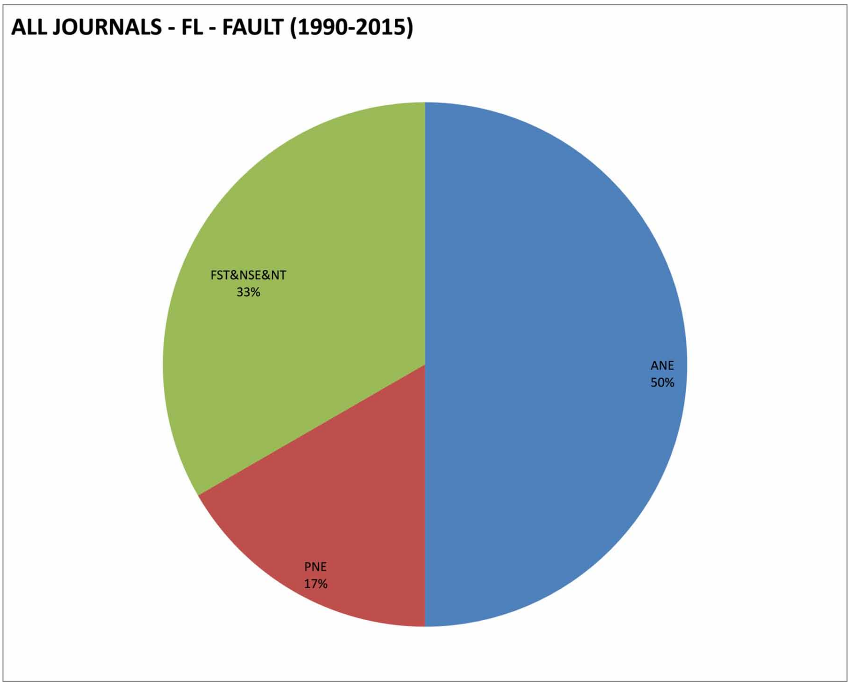


Figure 6a. Yearly percentage (% over the period 1990-2015) of purely monitoring-focused publications using the ANN exponent

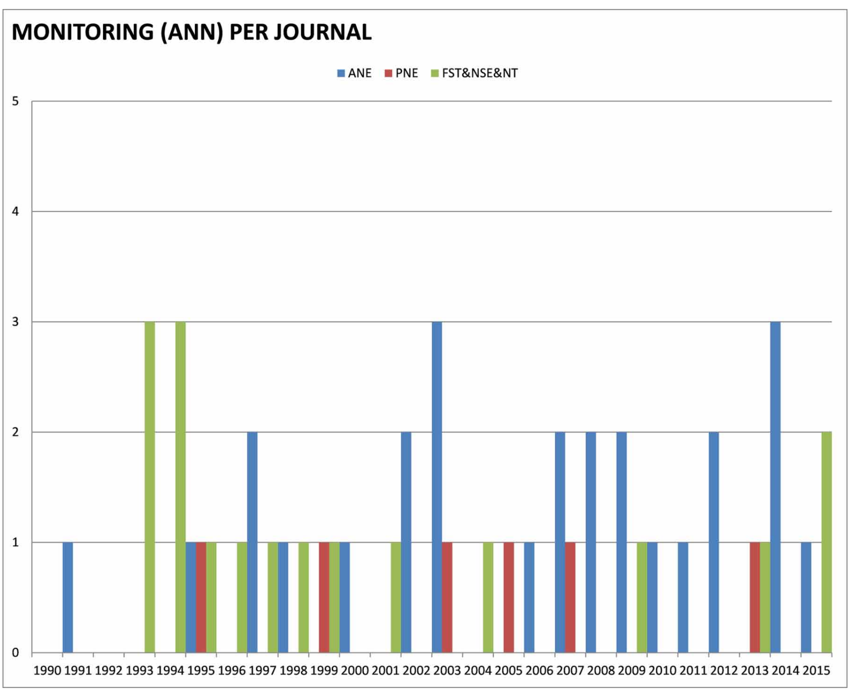


Figure 6b. Yearly percentage (% over the period 1990-2015) of purely monitoring-focused publications using the ANN exponent

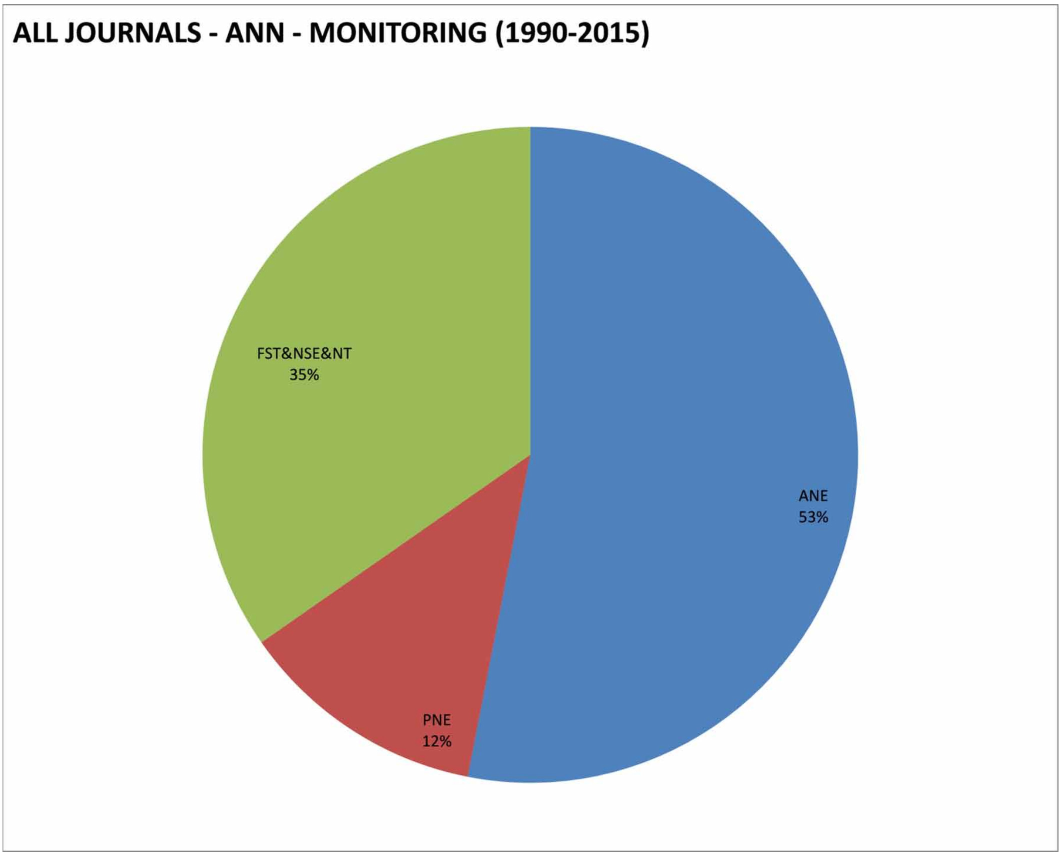


Figure 6c. Yearly percentage (% over the period 1990-2015) of purely monitoring-focused publications using the FL exponent

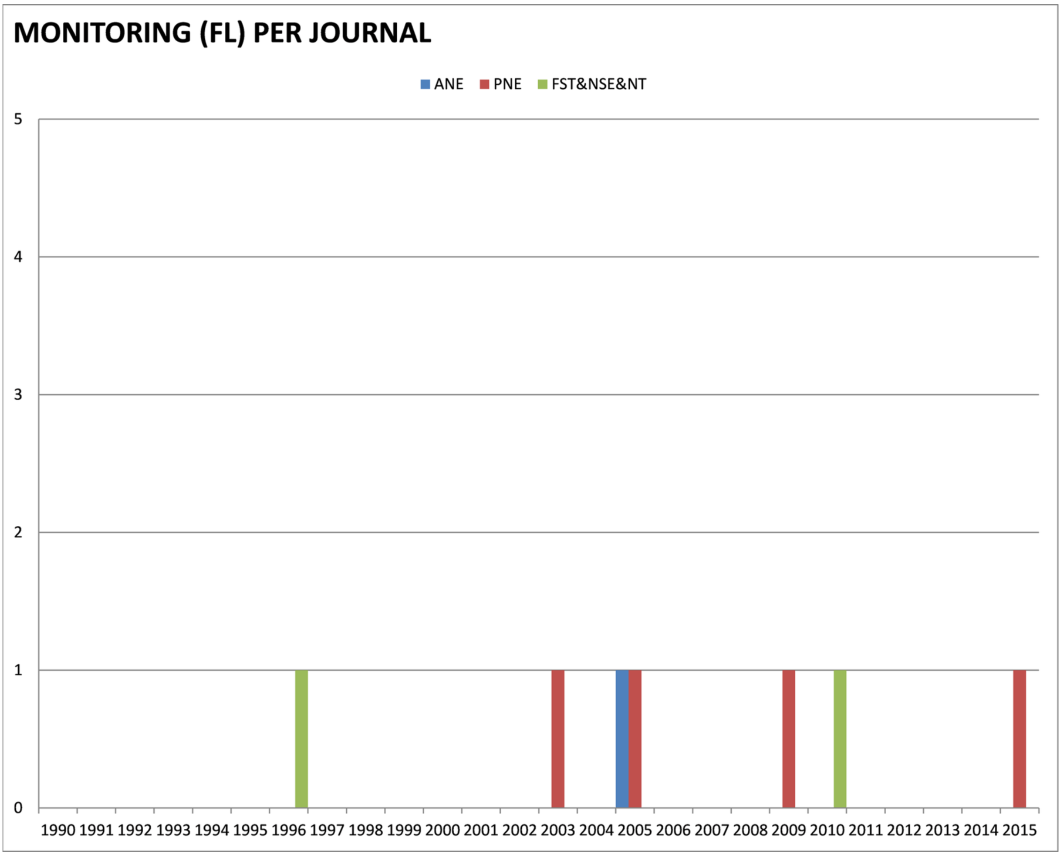


Figure 6d. Yearly percentage (% over the period 1990-2015) of purely monitoring-focused publications using the FL exponent

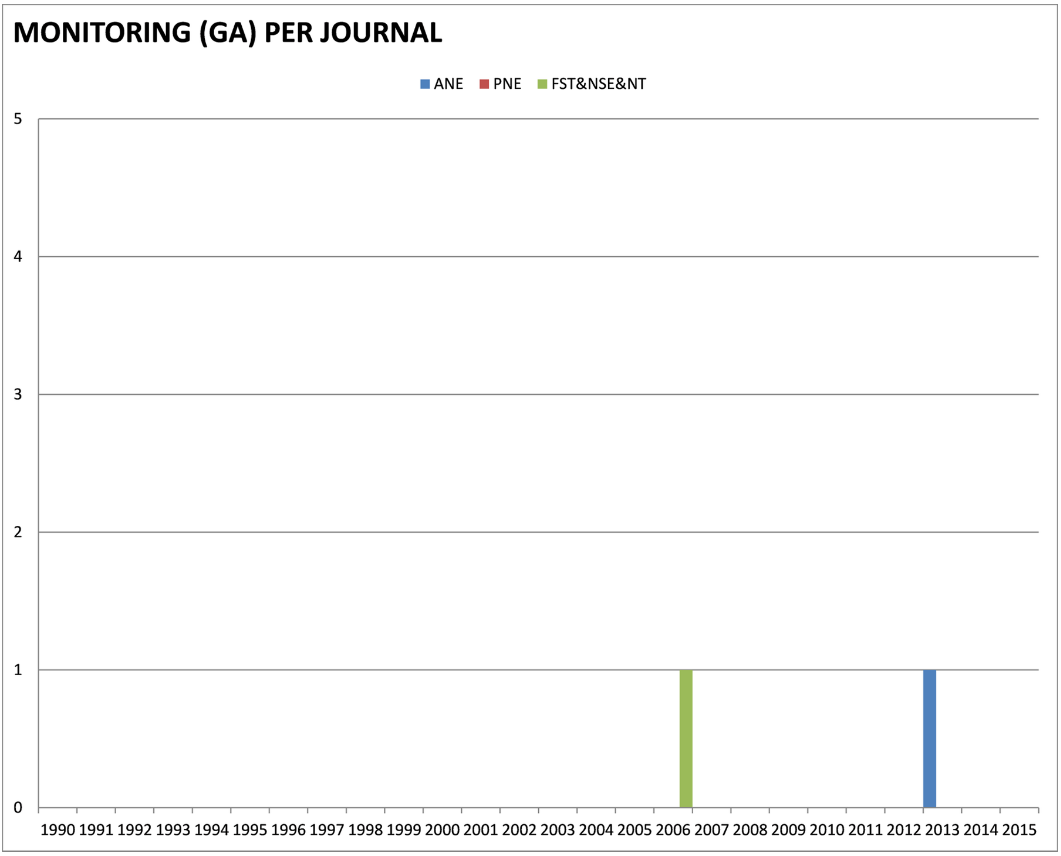


Figure 6e. Yearly percentage (% over the period 1990-2015) of purely monitoring-focused publications using the GA exponent

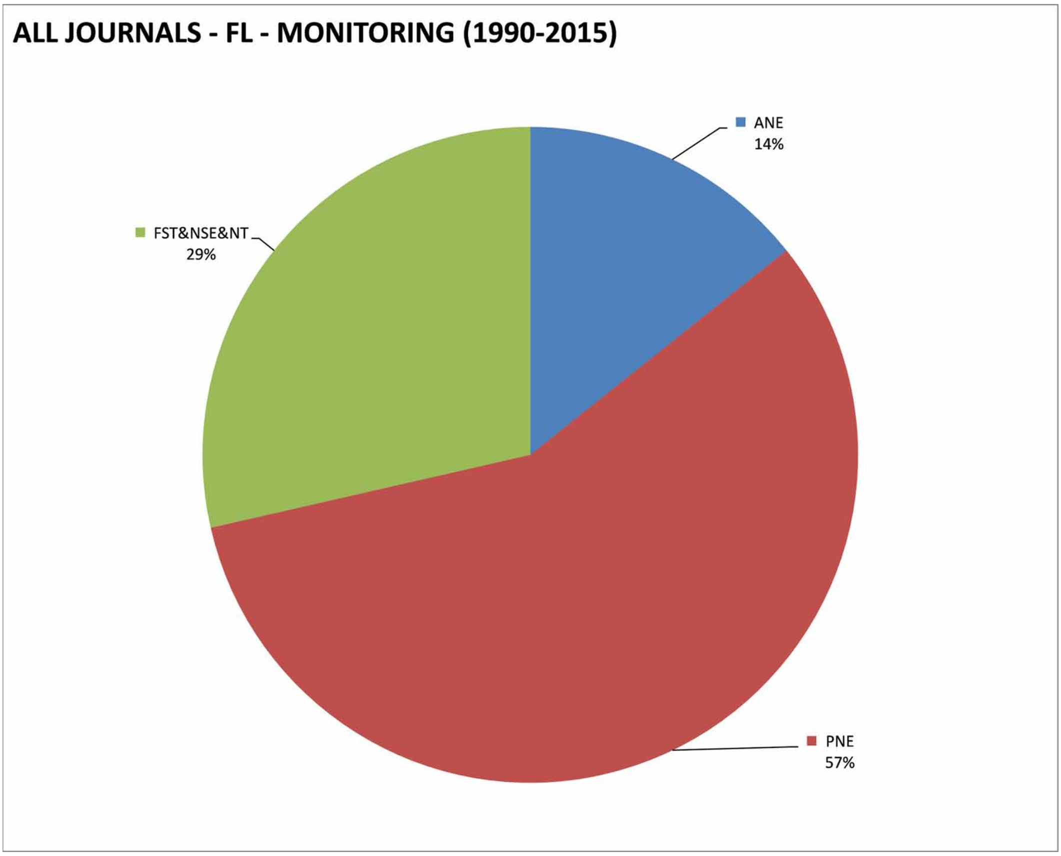


Figure 6f. Yearly percentage (% over the period 1990-2015) of purely monitoring-focused publications using the GA exponent

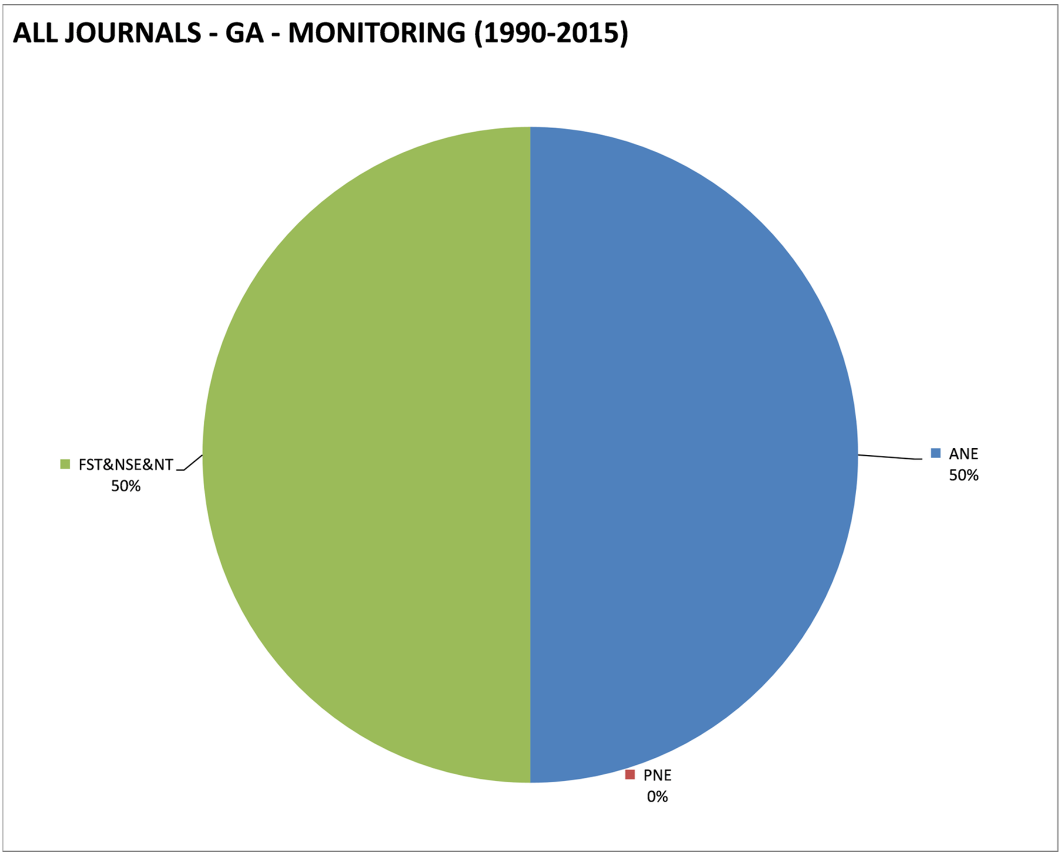


Figure 7a. Yearly percentage (% over the period 1990-2015) of purely NPP operations-focused publications using the ANN exponent

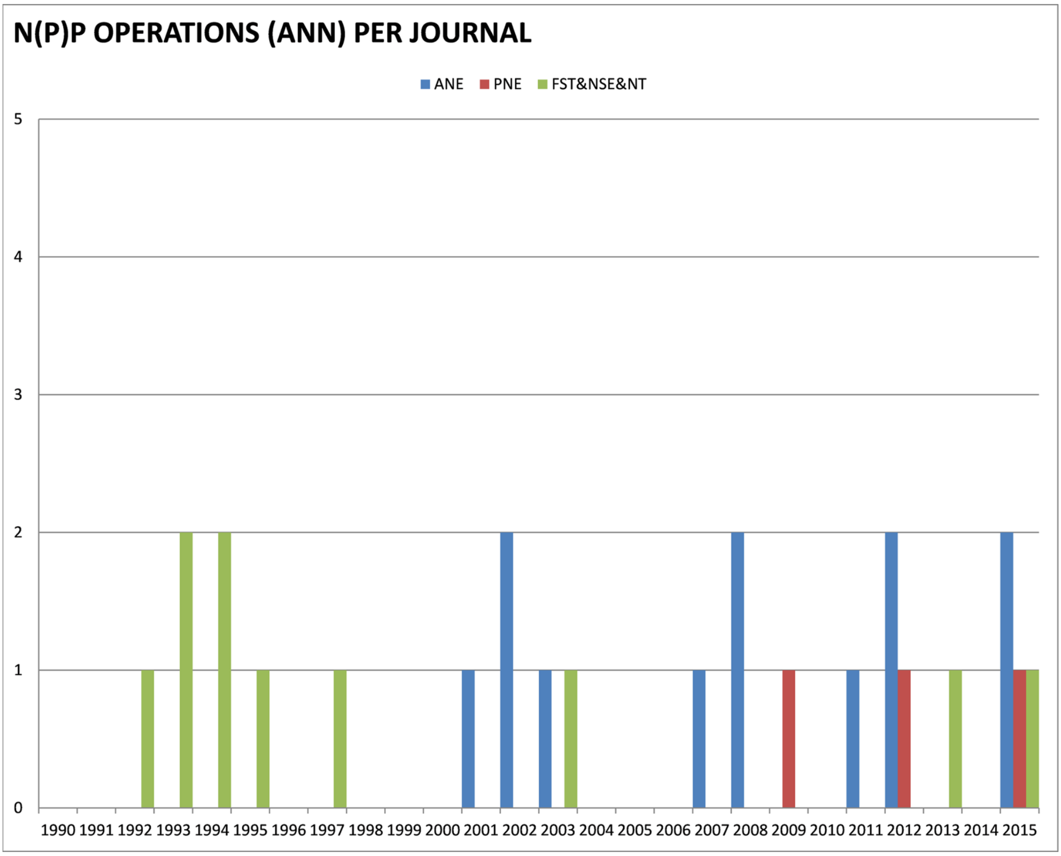


Figure 7b. Yearly percentage (% over the period 1990-2015) of purely NPP operations-focused publications using the ANN exponent

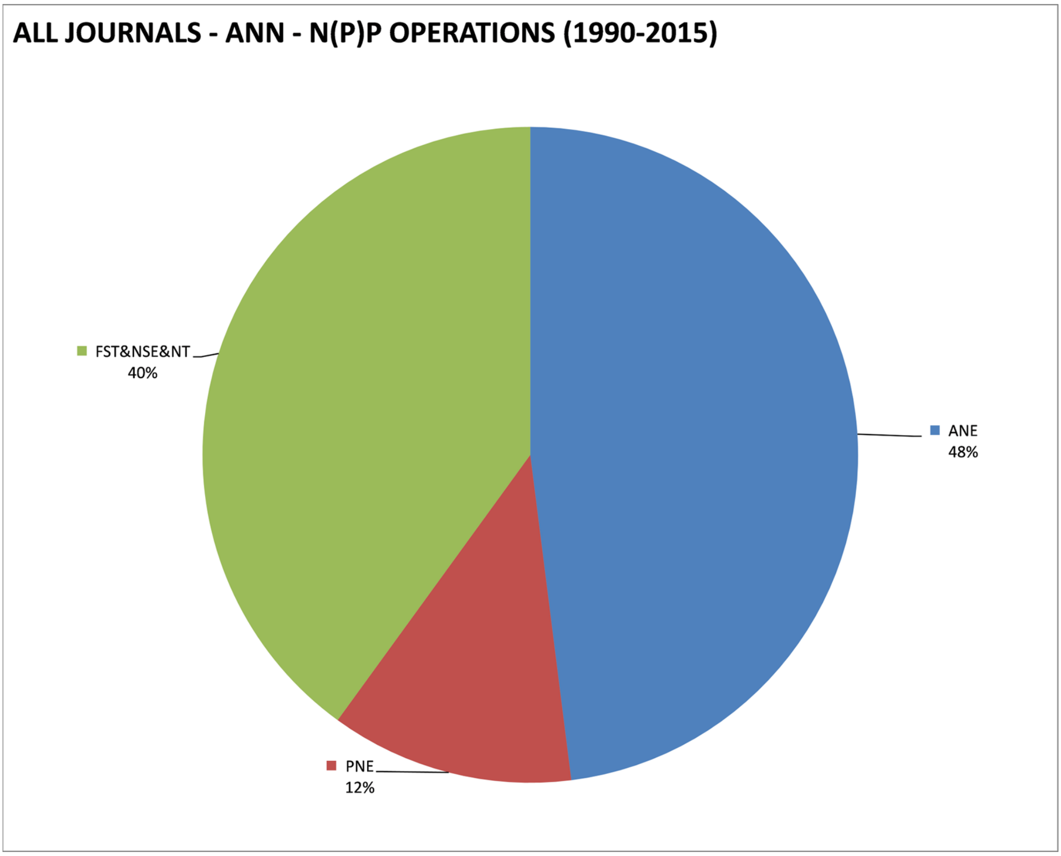


Figure 7c. Yearly percentage (% over the period 1990-2015) of purely NPP operations-focused publications using the FL exponent

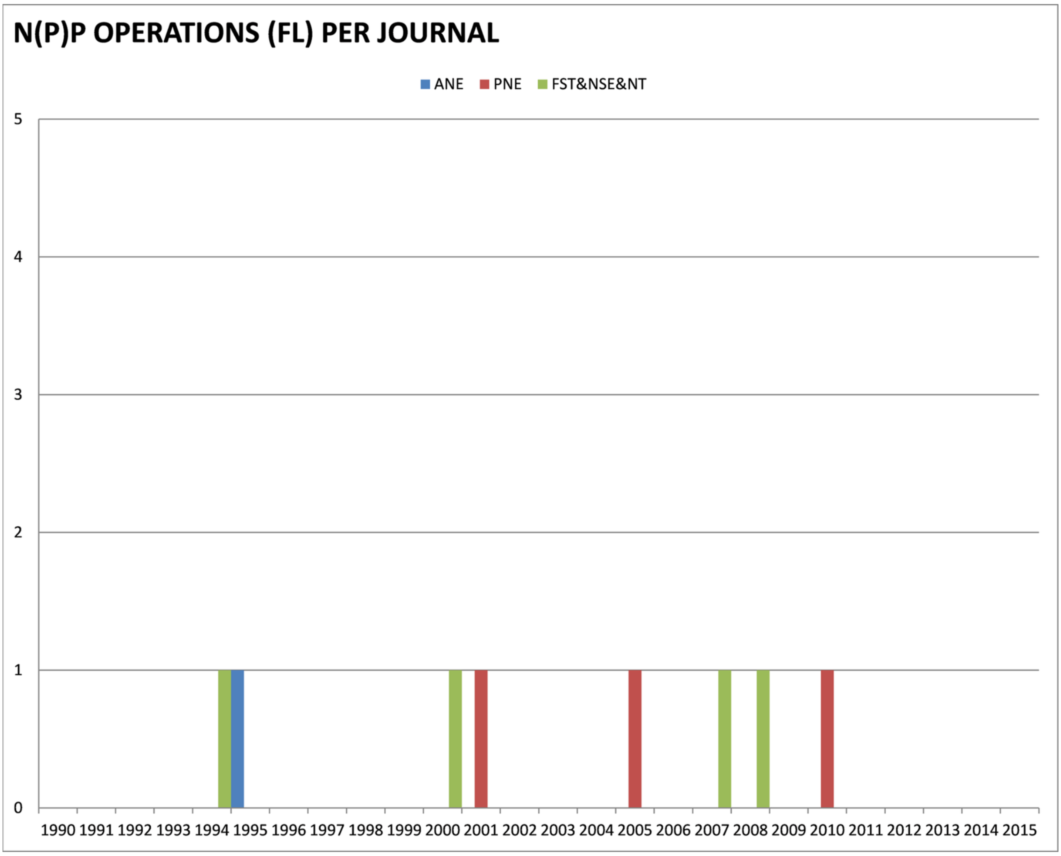


Figure 7d. Yearly percentage (% over the period 1990-2015) of purely NPP operations-focused publications using the FL exponent

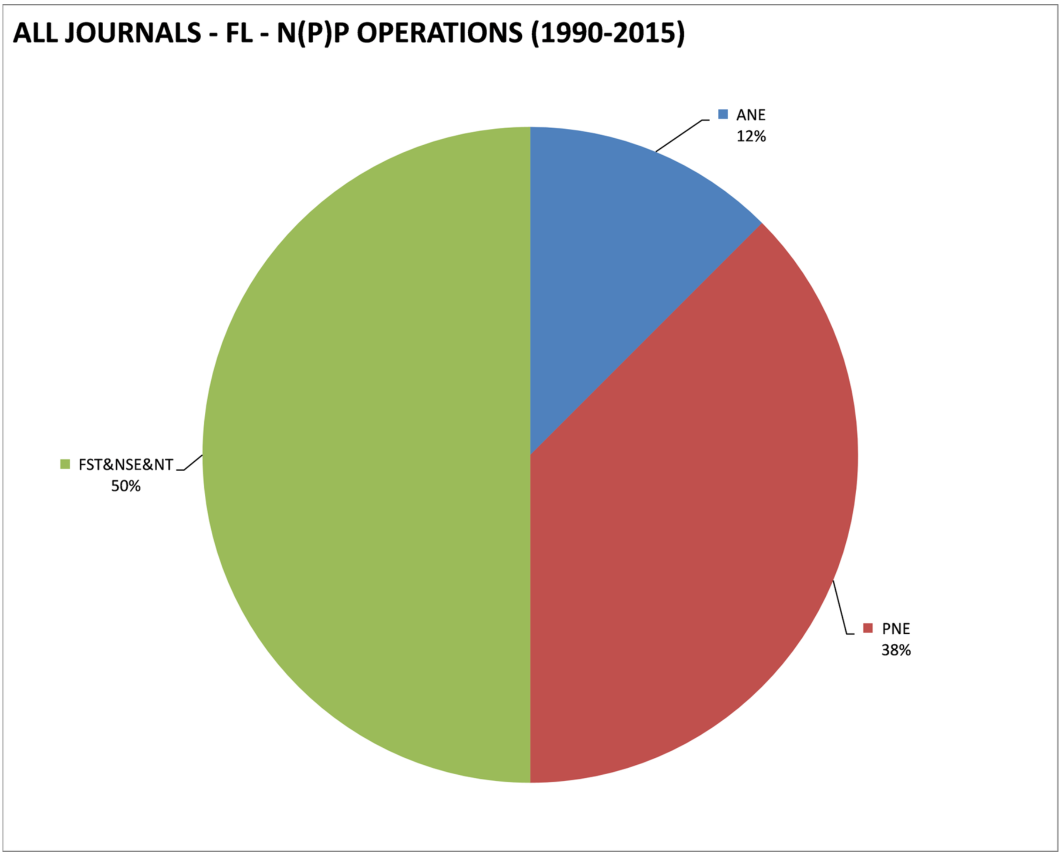


Figure 7e. Yearly percentage (% over the period 1990-2015) of purely NPP operations-focused publications using the GA exponent

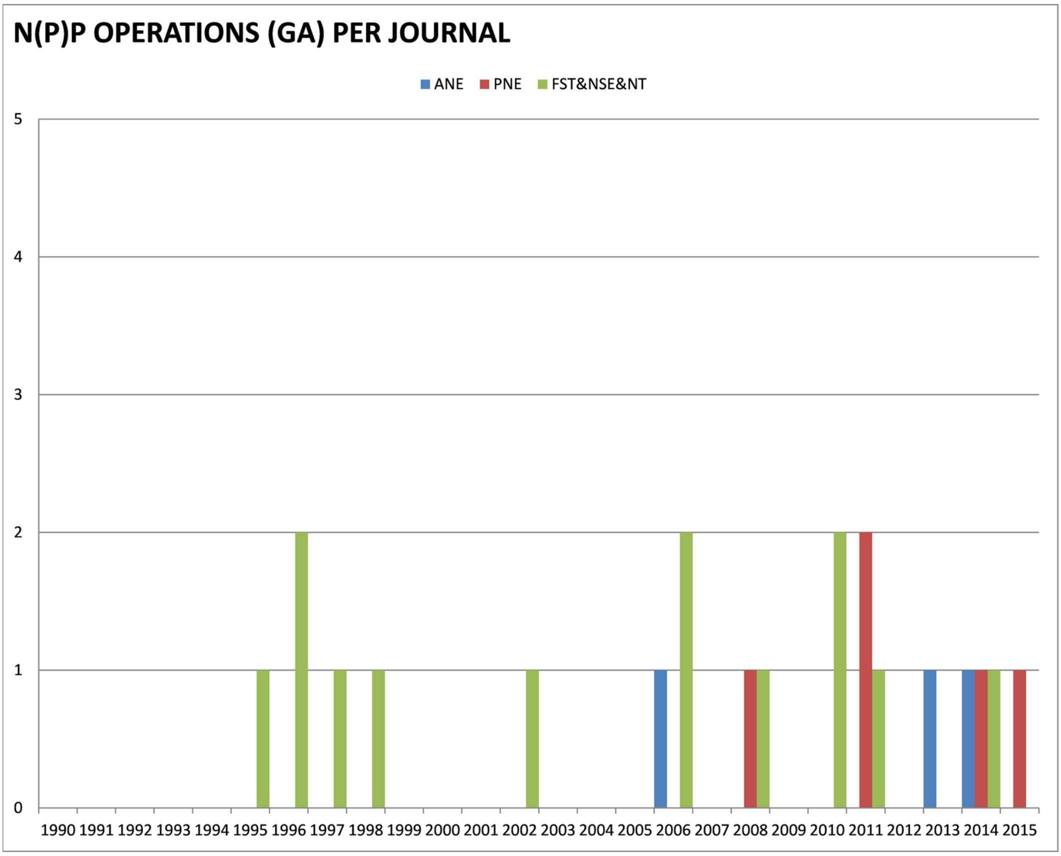


Figure 7f. Yearly percentage (% over the period 1990-2015) of purely NPP operations-focused publications using the GA exponent

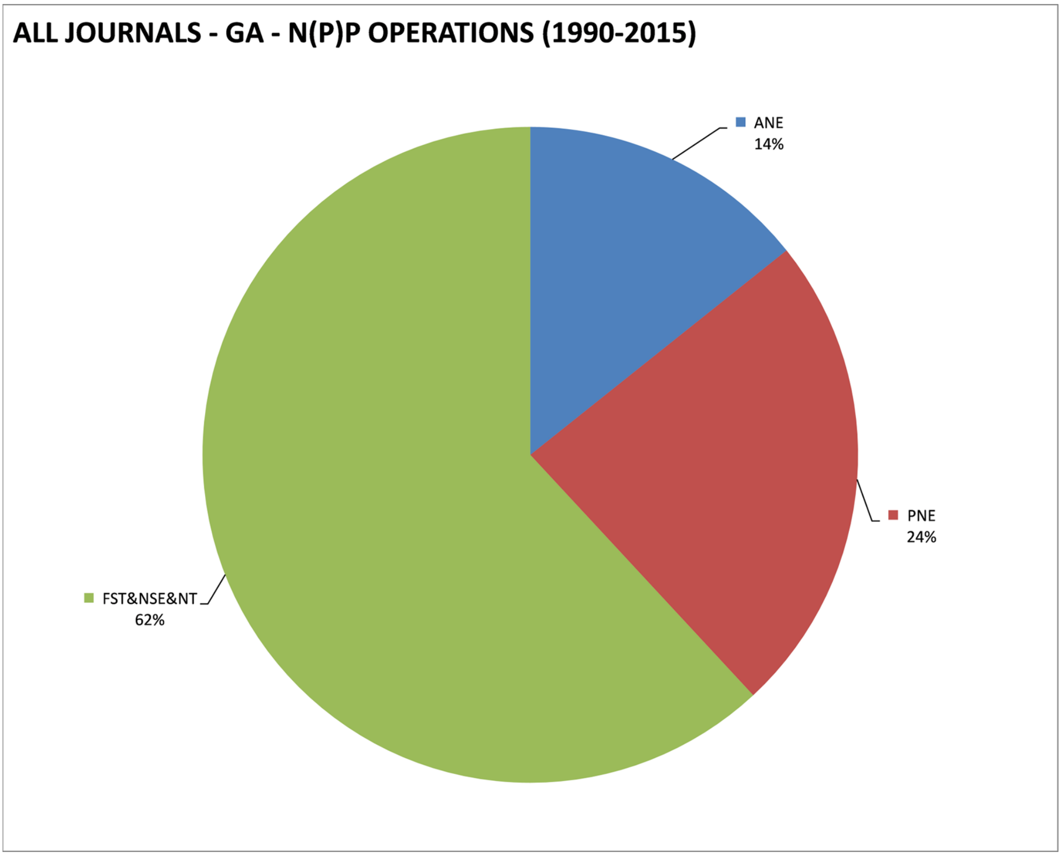


Figure 8a. Yearly percentage (% over the period 1990-2015) of purely proliferation and resistance applications-focused publications using the ANN exponents

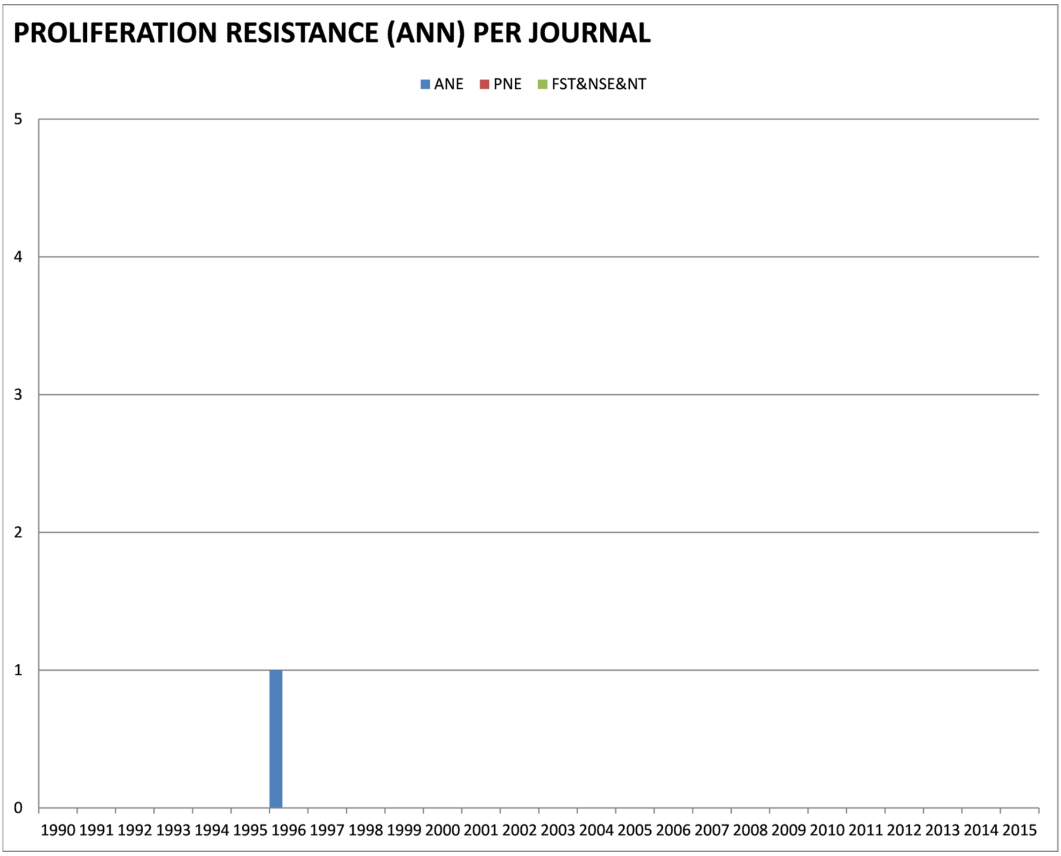


Figure 8b. Yearly percentage (% over the period 1990-2015) of purely proliferation and resistance applications-focused publications using the ANN exponents

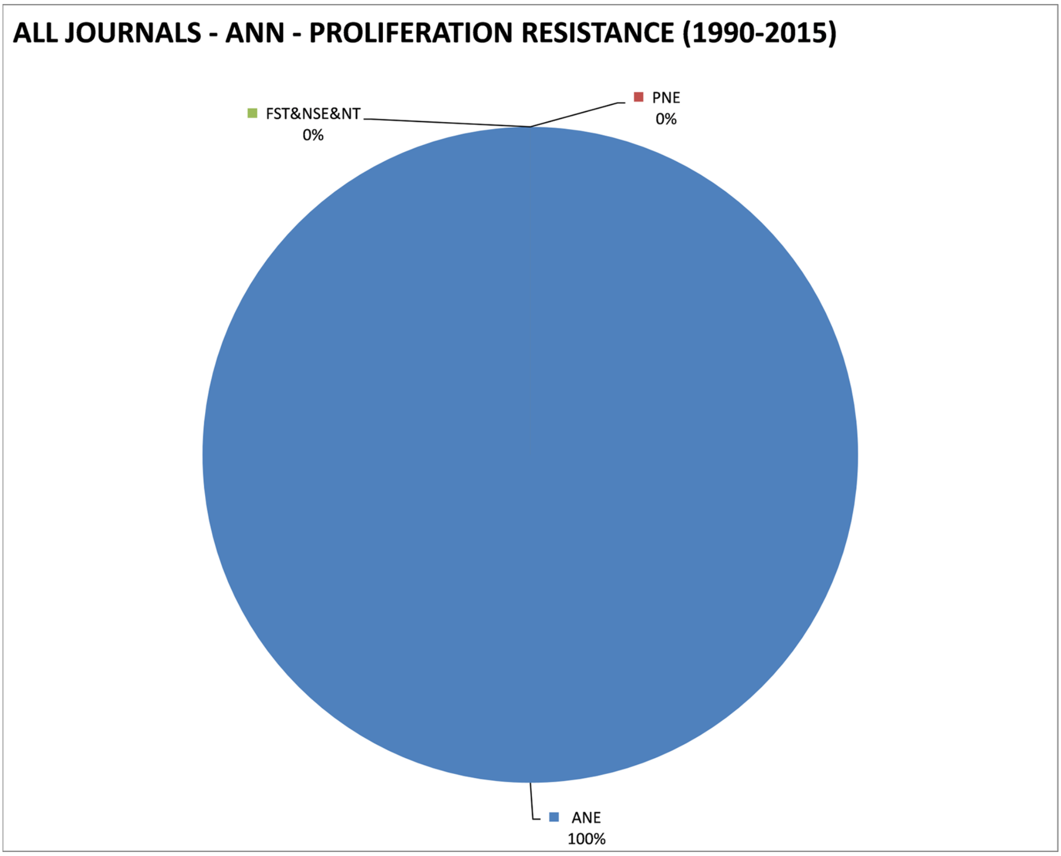


Figure 8c. Yearly percentage (% over the period 1990-2015) of purely proliferation and resistance applications-focused publications using the FL exponents

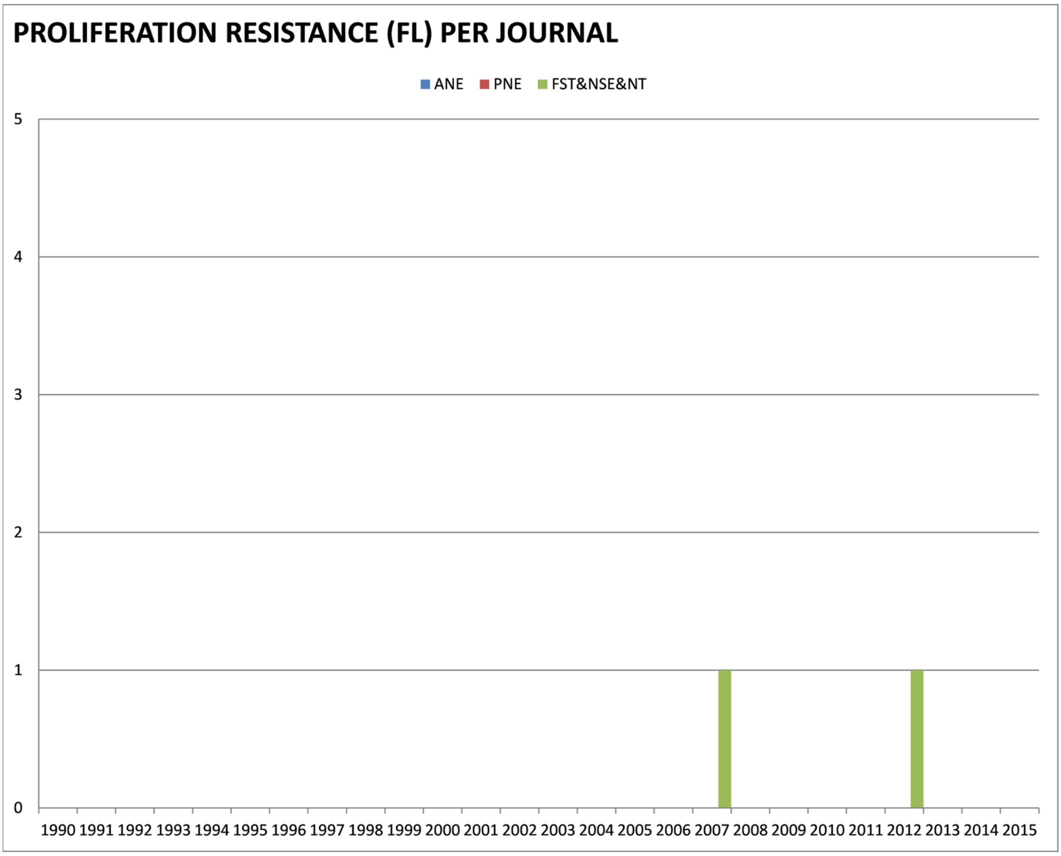


Figure 8d. Yearly percentage (% over the period 1990-2015) of purely proliferation and resistance applications-focused publications using the FL exponents

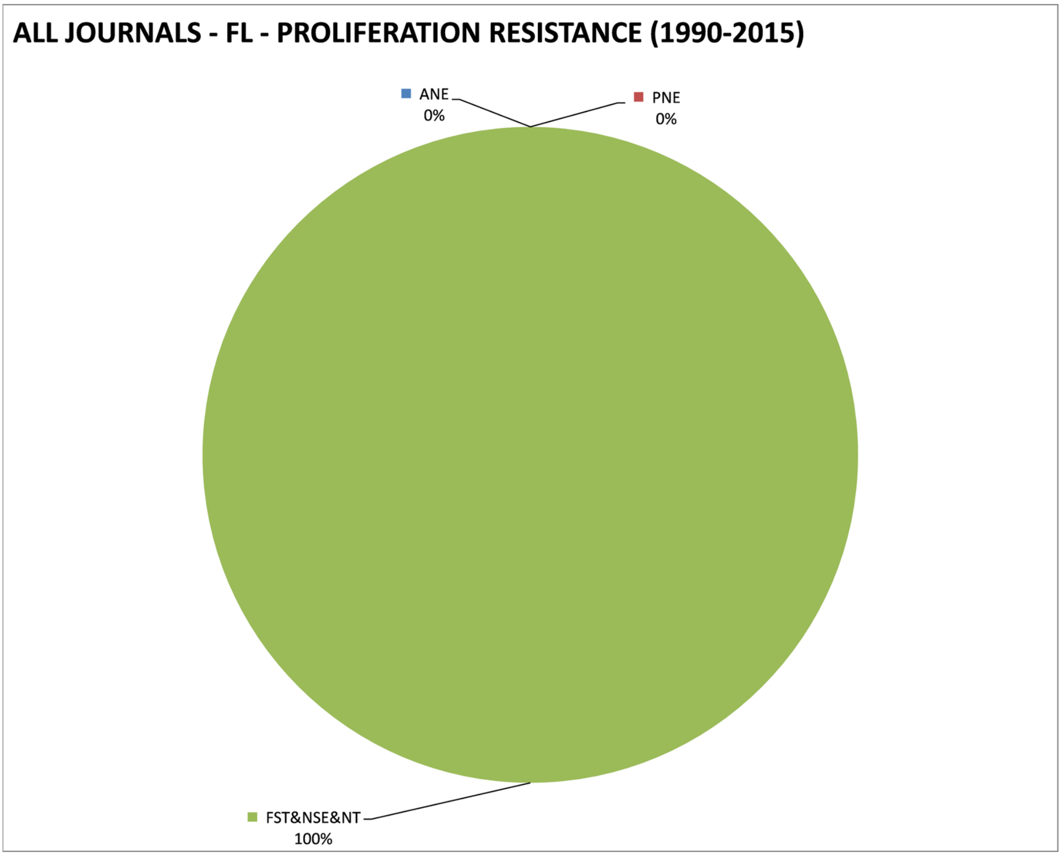


Figure 9a. Yearly percentage (% over the period 1990-2015) of purely sensor and component reliability publications using the ANN exponents

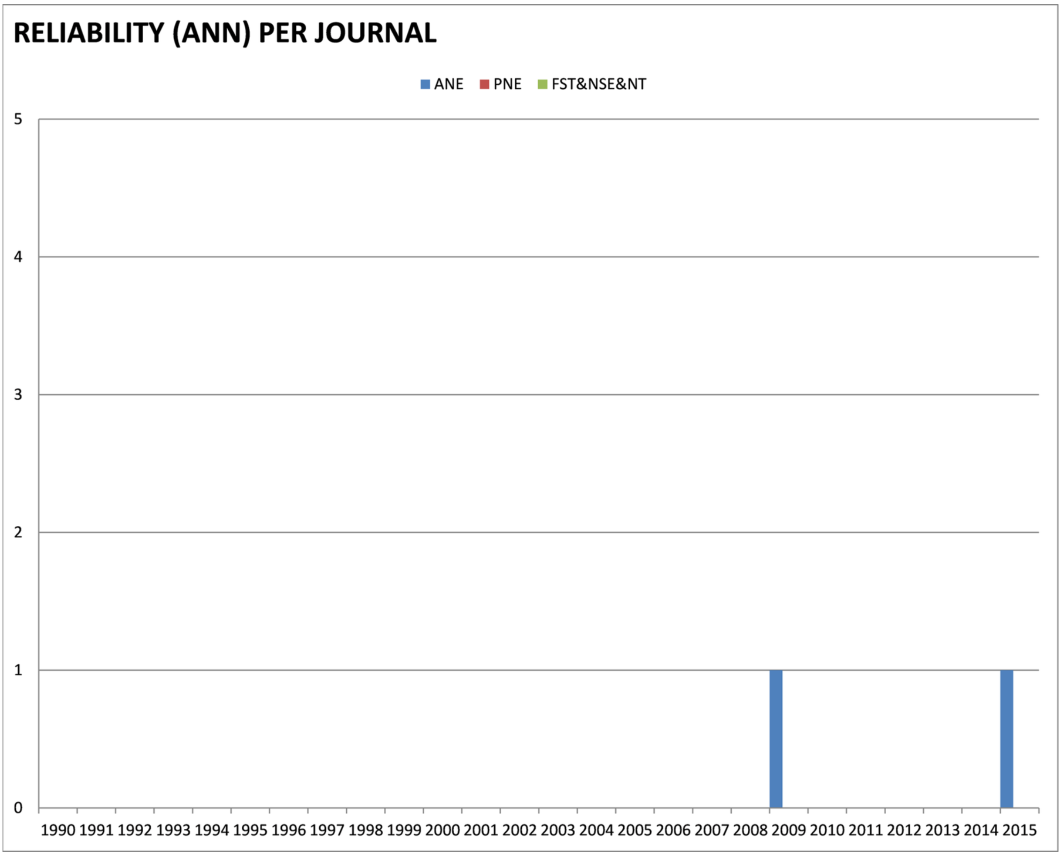


Figure 9b. Yearly percentage (% over the period 1990-2015) of purely sensor and component reliability publications using the ANN exponents

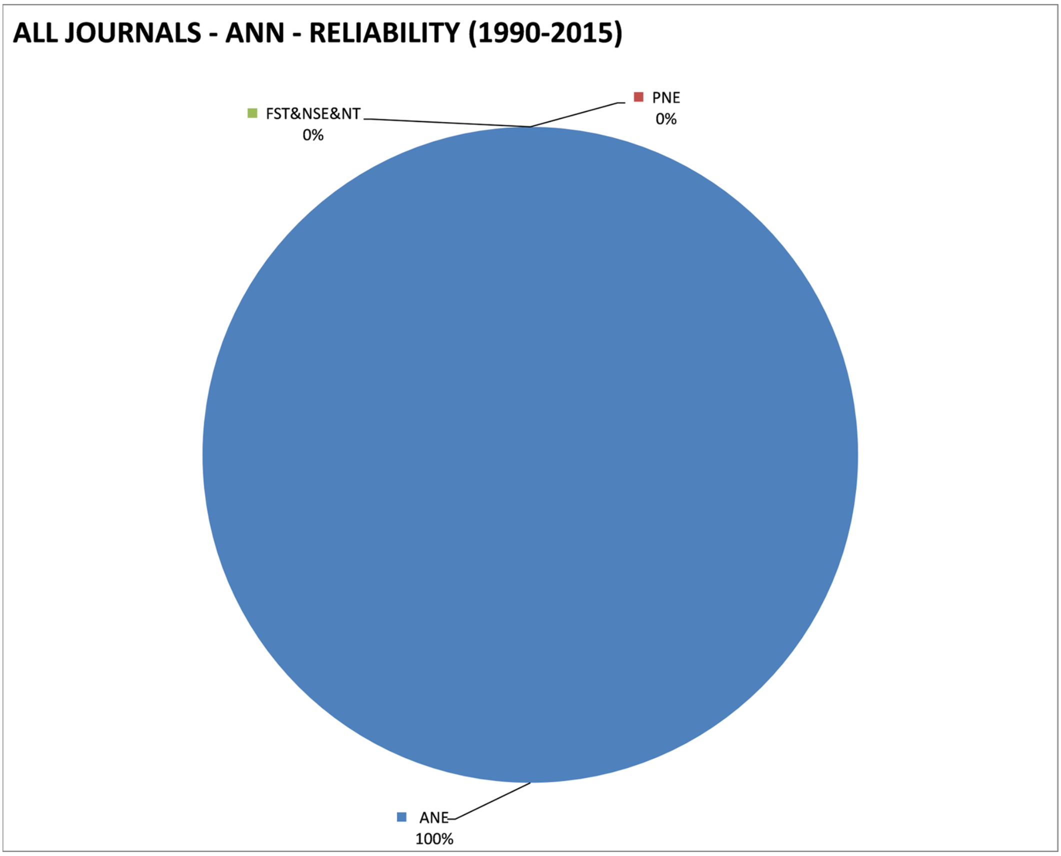


Figure 9c. Yearly percentage (% over the period 1990-2015) of purely sensor and component reliability publications using the FL exponents

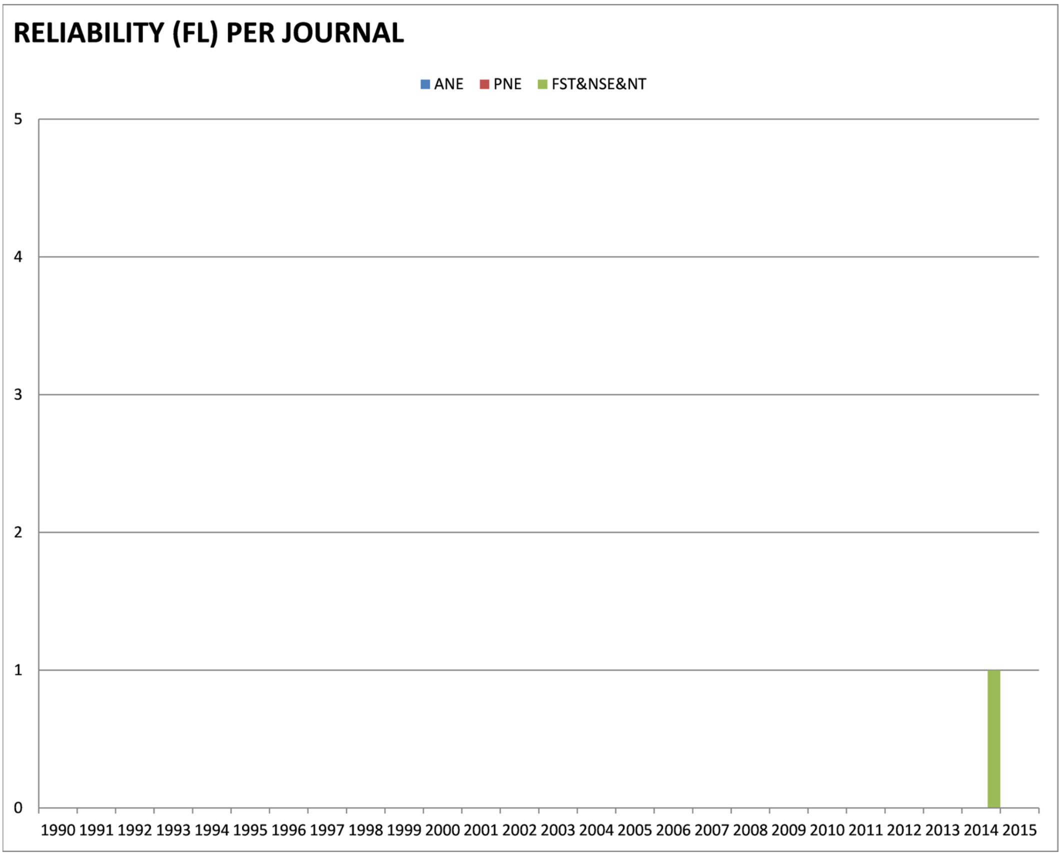


Figure 9d. Yearly percentage (% over the period 1990-2015) of purely sensor and component reliability publications using the FL exponents

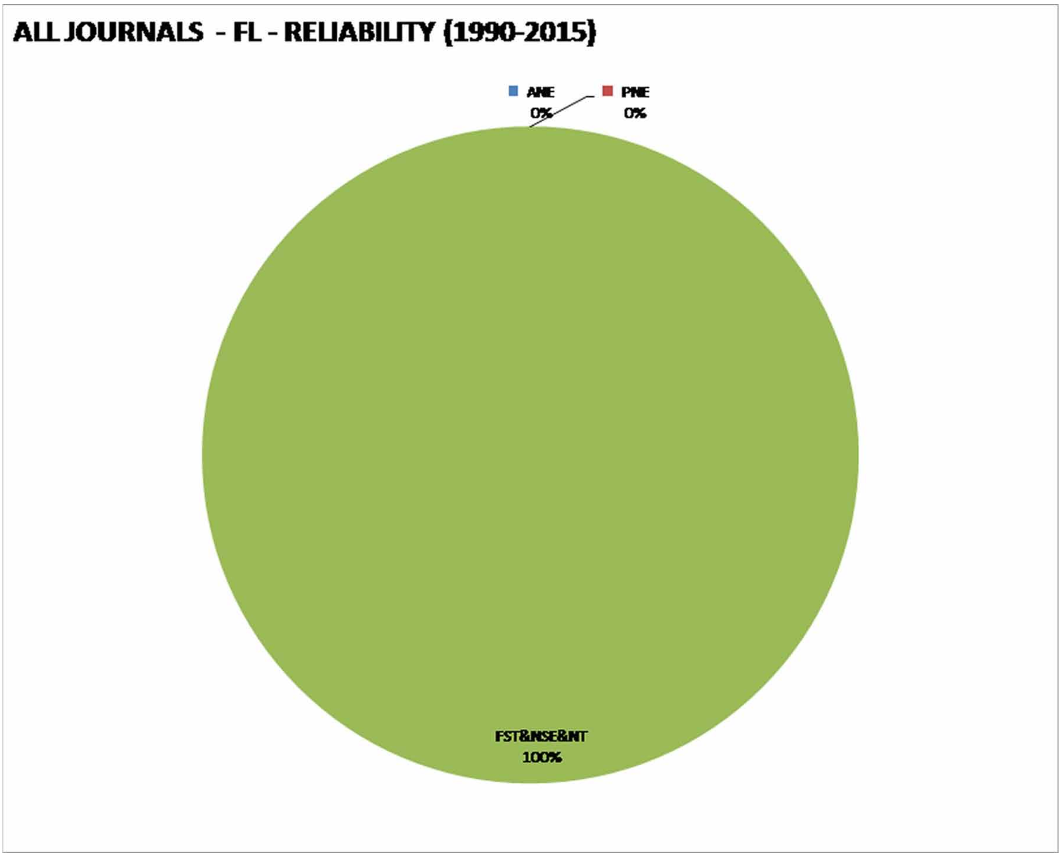


Figure 10a. Yearly percentage (% over the period 1990-2015) of purely Spectroscopy publications using the ANN exponents

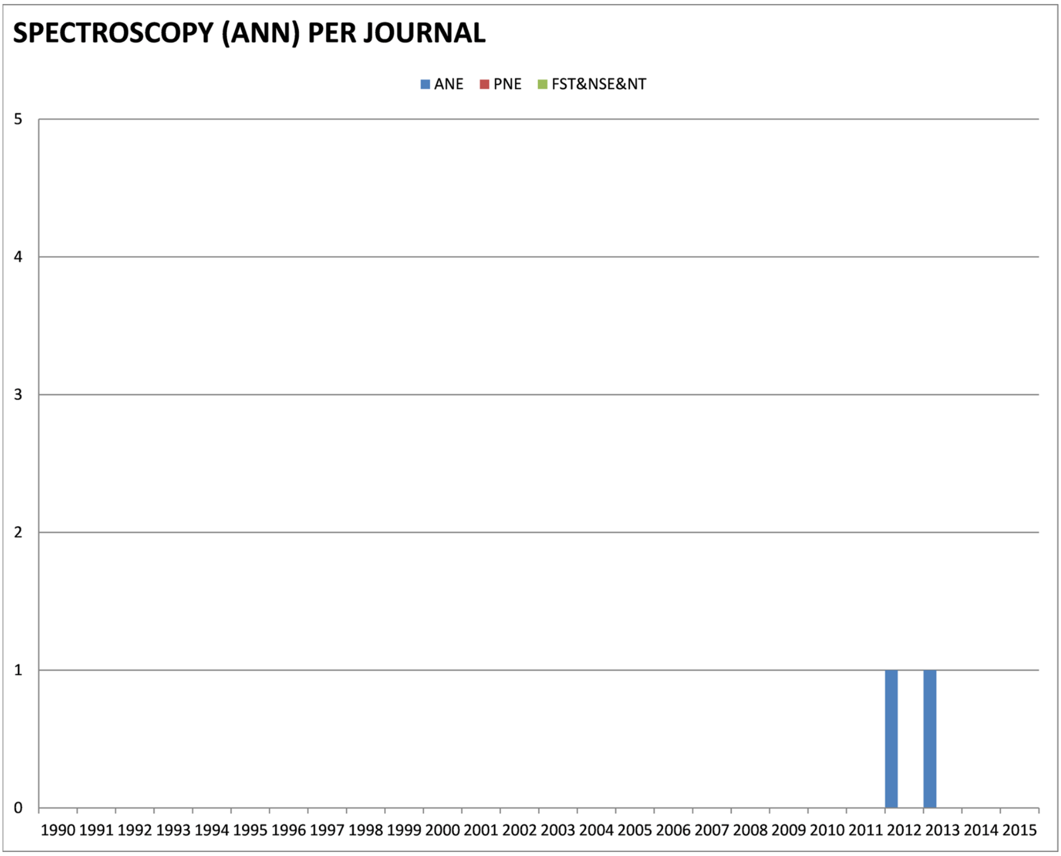


Figure 10b. Yearly percentage (% over the period 1990-2015) of purely Spectroscopy publications using the FL exponents

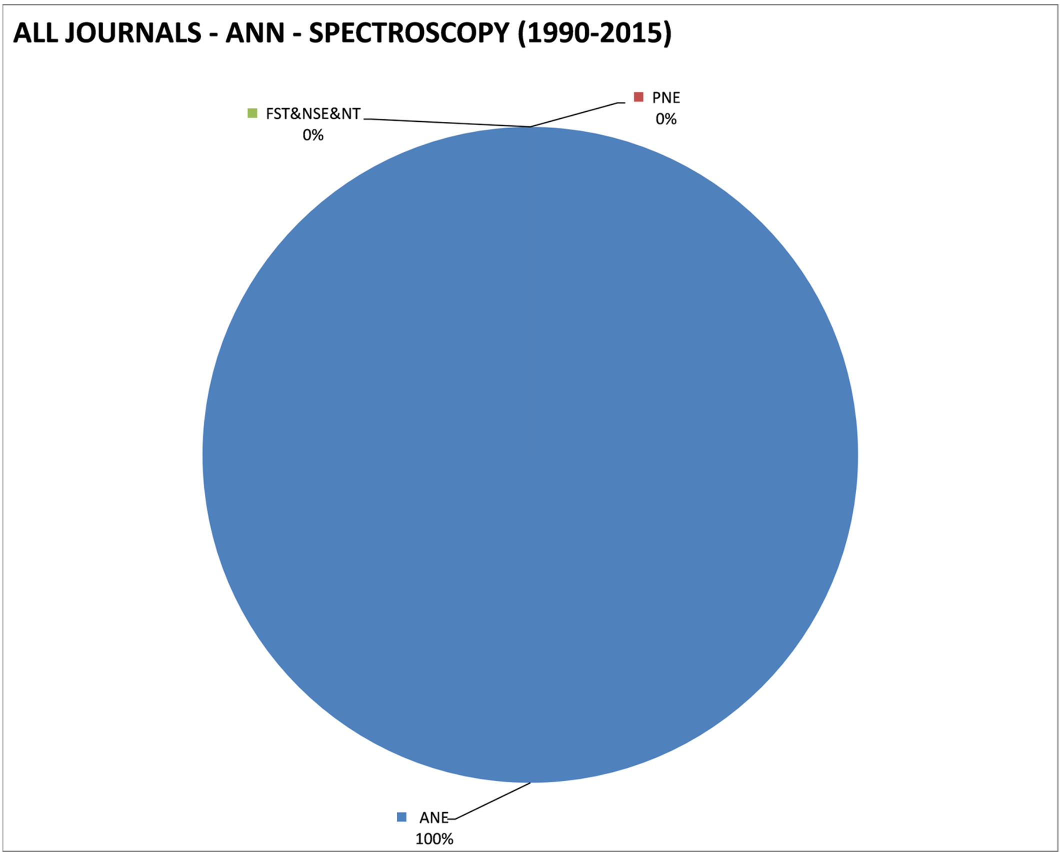


Figure 10c. Yearly percentage (% over the period 1990-2015) of purely Spectroscopy publications using the FL exponents

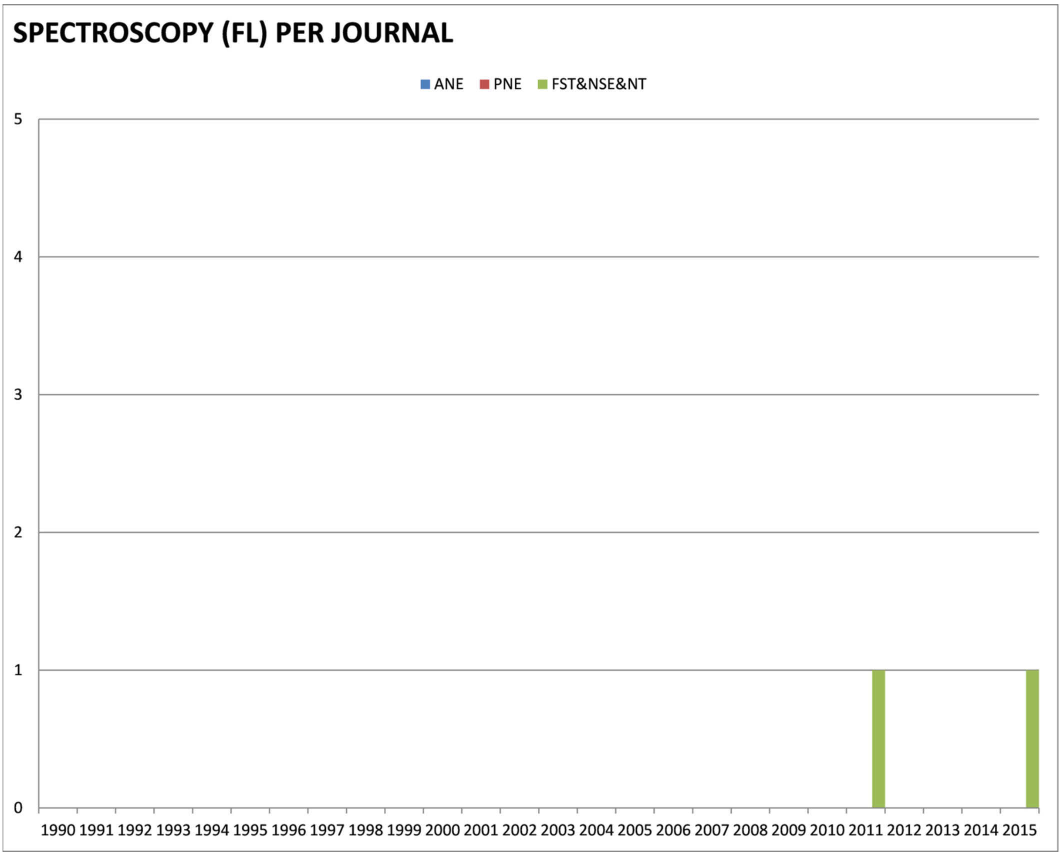


Figure 10d. All journals:FL Spectroscopy

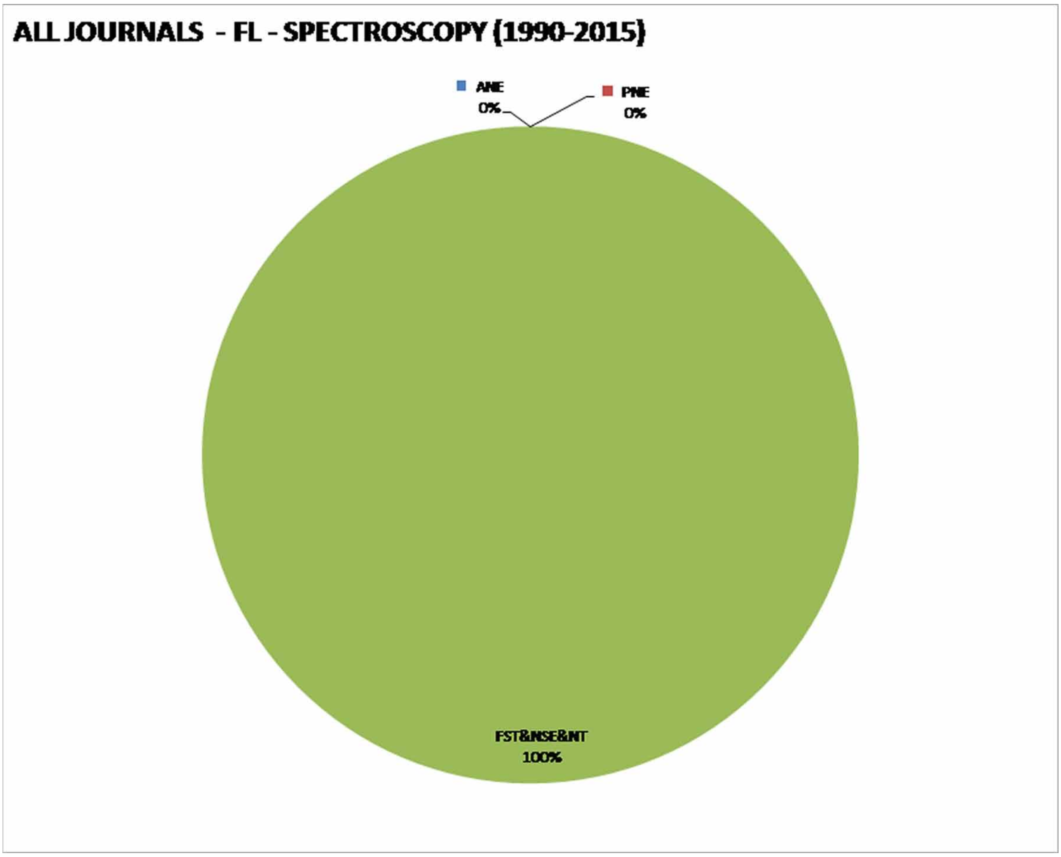


Figure 10e. Spectroscopy (GA) per journal

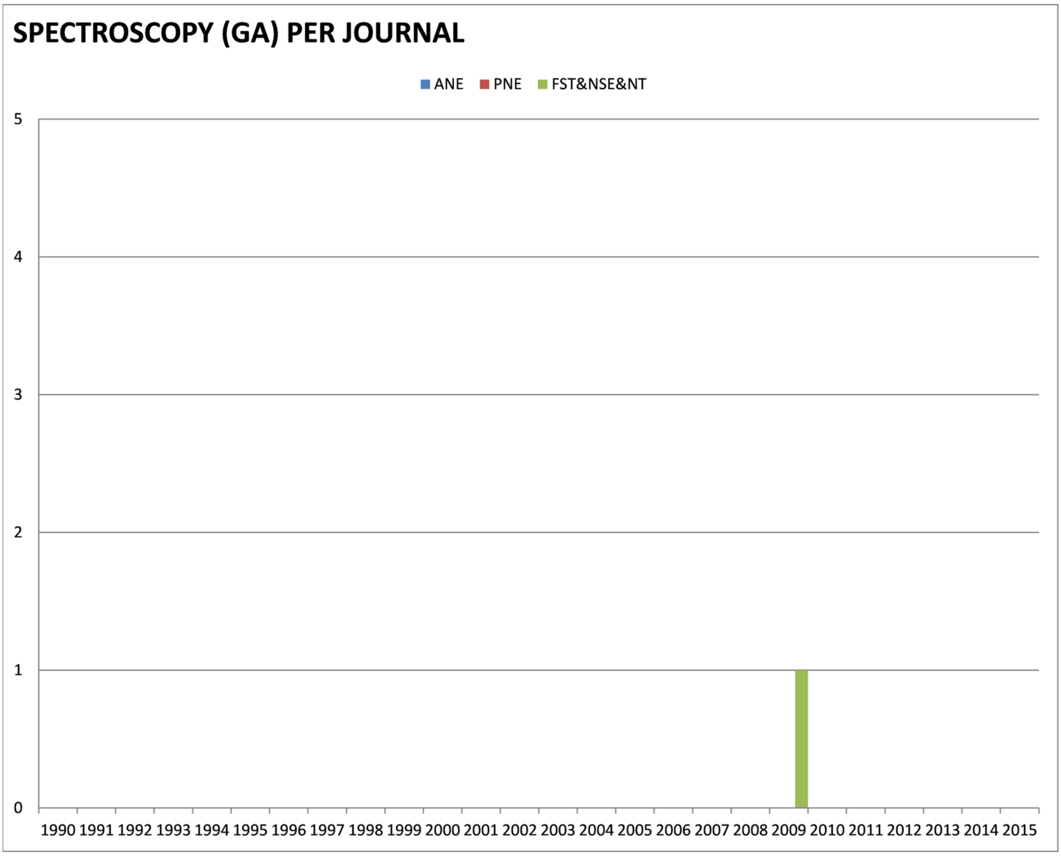


Figure 10f. All journals: GA Spectroscopy

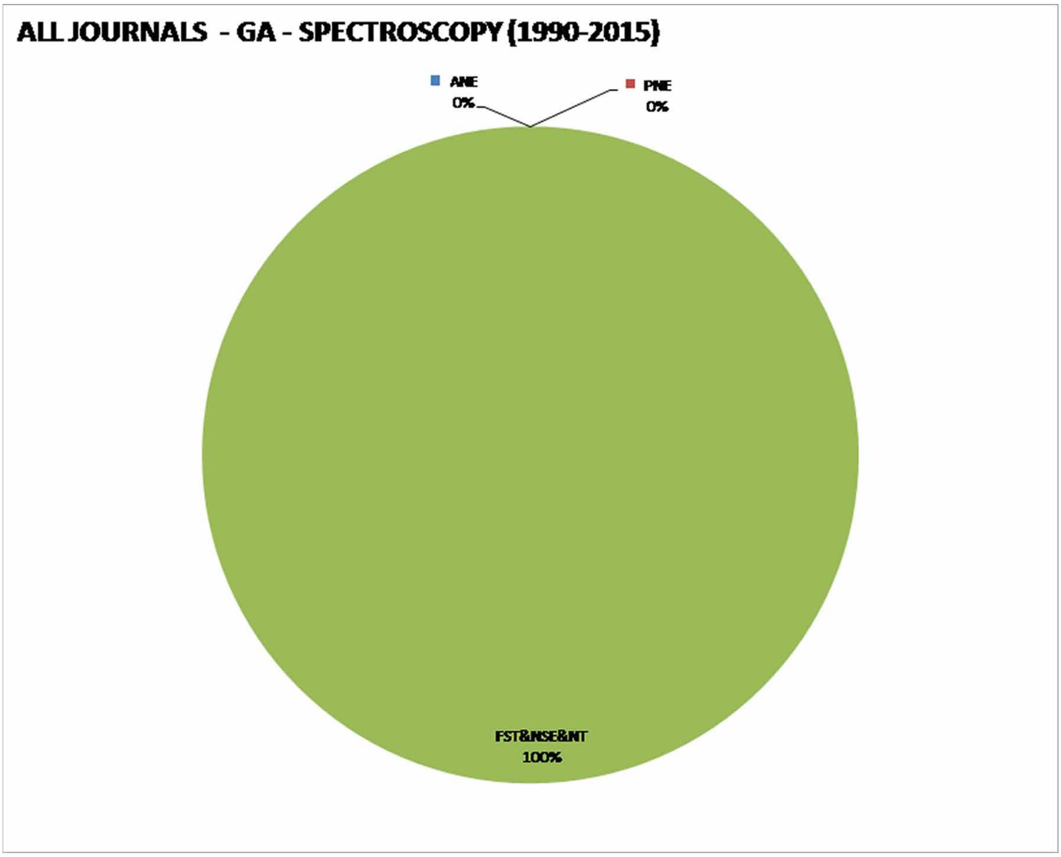


Figure 11a. Yearly percentage (% over the period 1990-2015) of purely fusion-focused publications using the ANN exponent

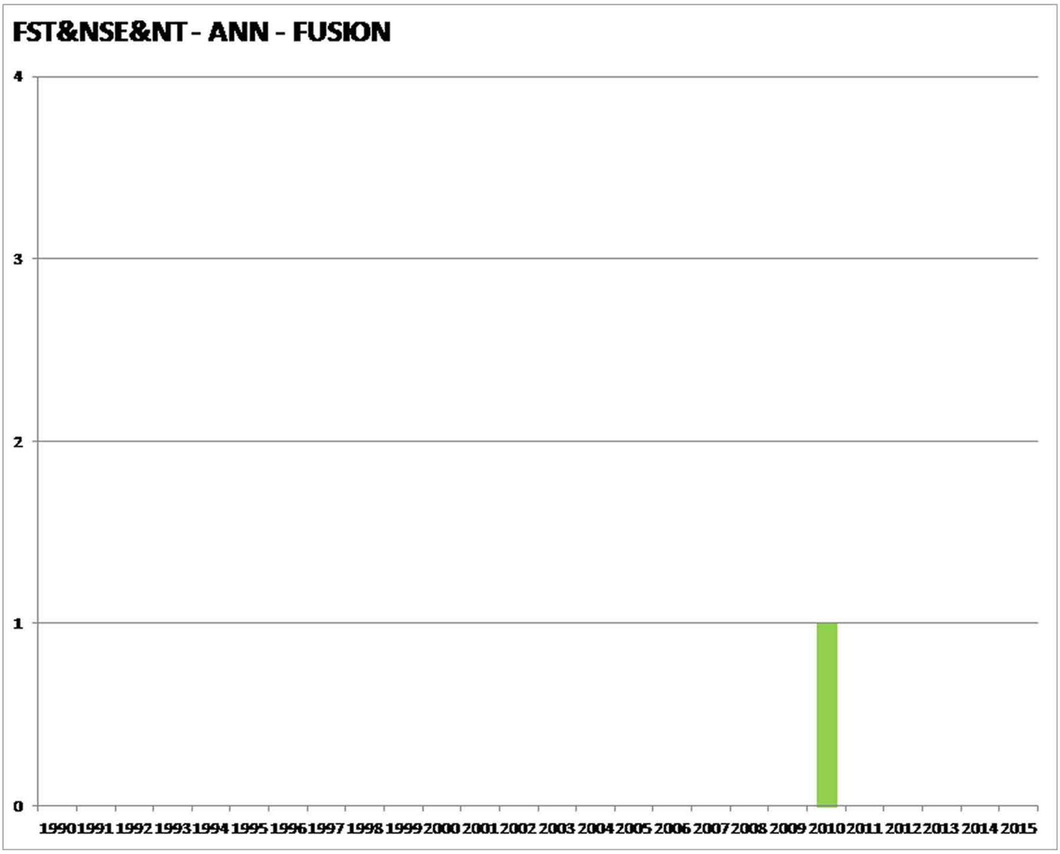


Figure 11b. Yearly percentage (% over the period 1990-2015) of purely fusion-focused publications using the ANN exponent

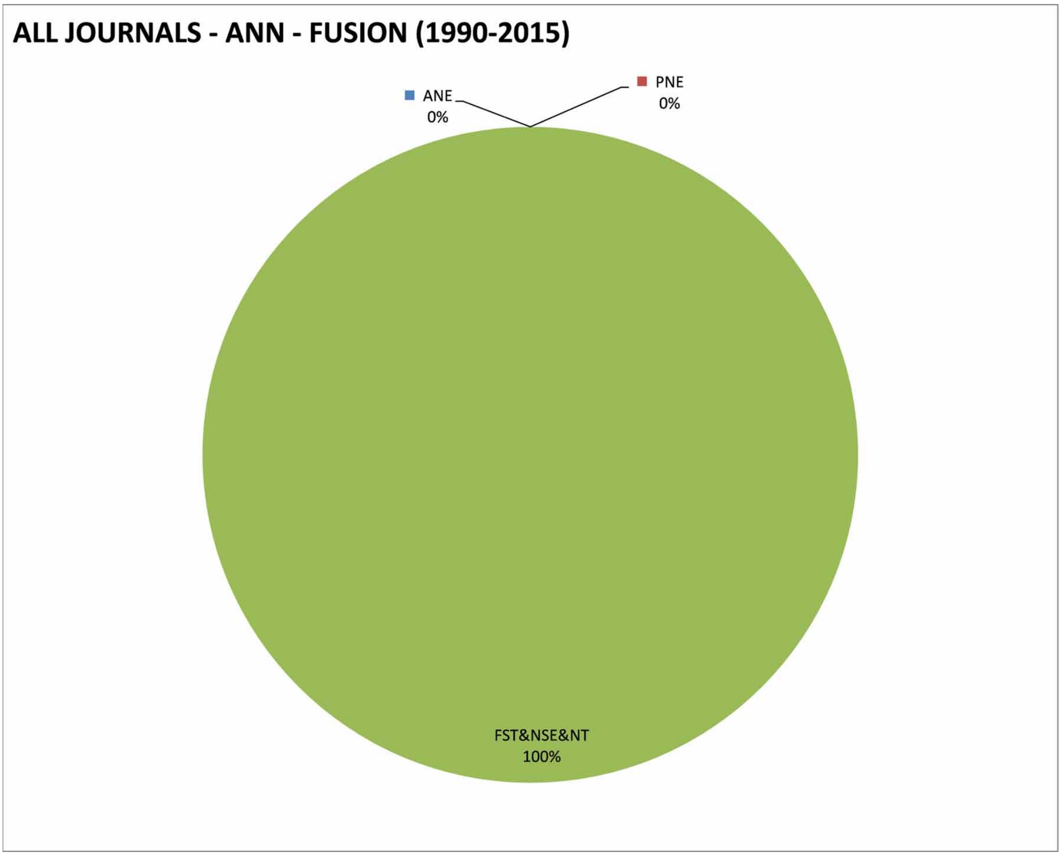


Figure 12a. Yearly percentage (% over the period 1990-2015) of publications involving CI combinations-focused publications grouped by publication medium

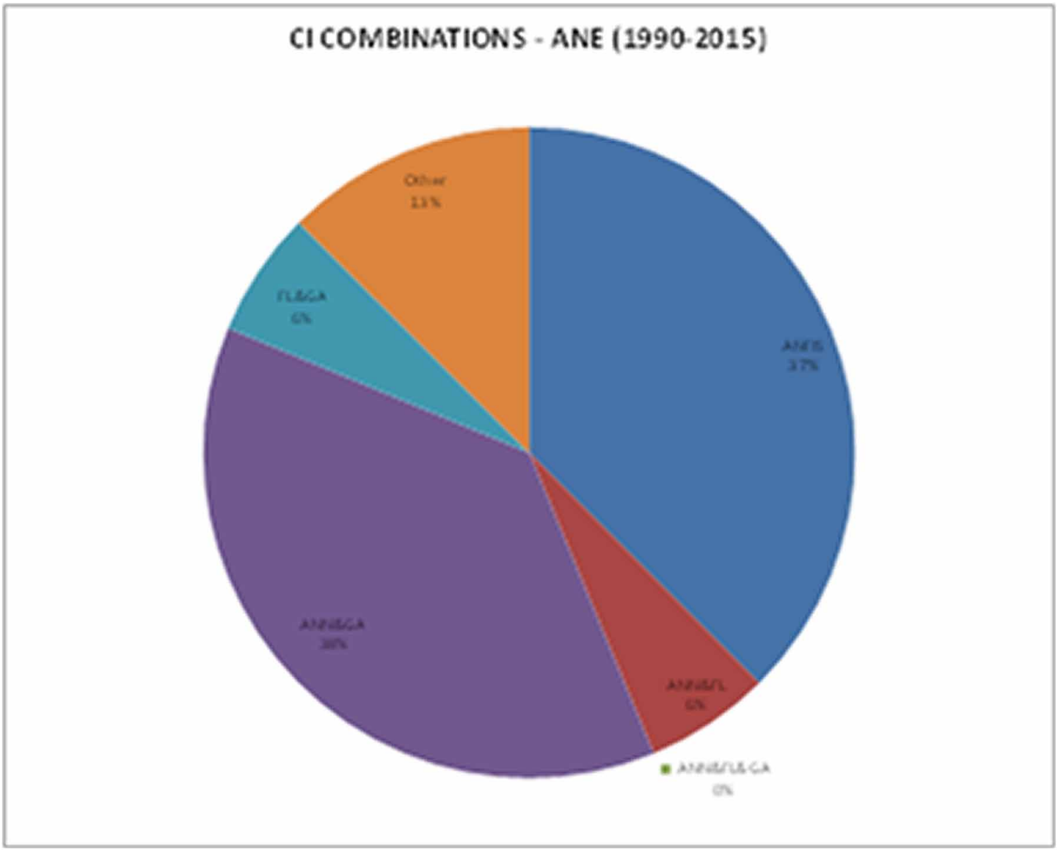


Figure 12b. Yearly percentage (% over the period 1990-2015) of publications involving CI combinations-focused publications grouped by publication medium

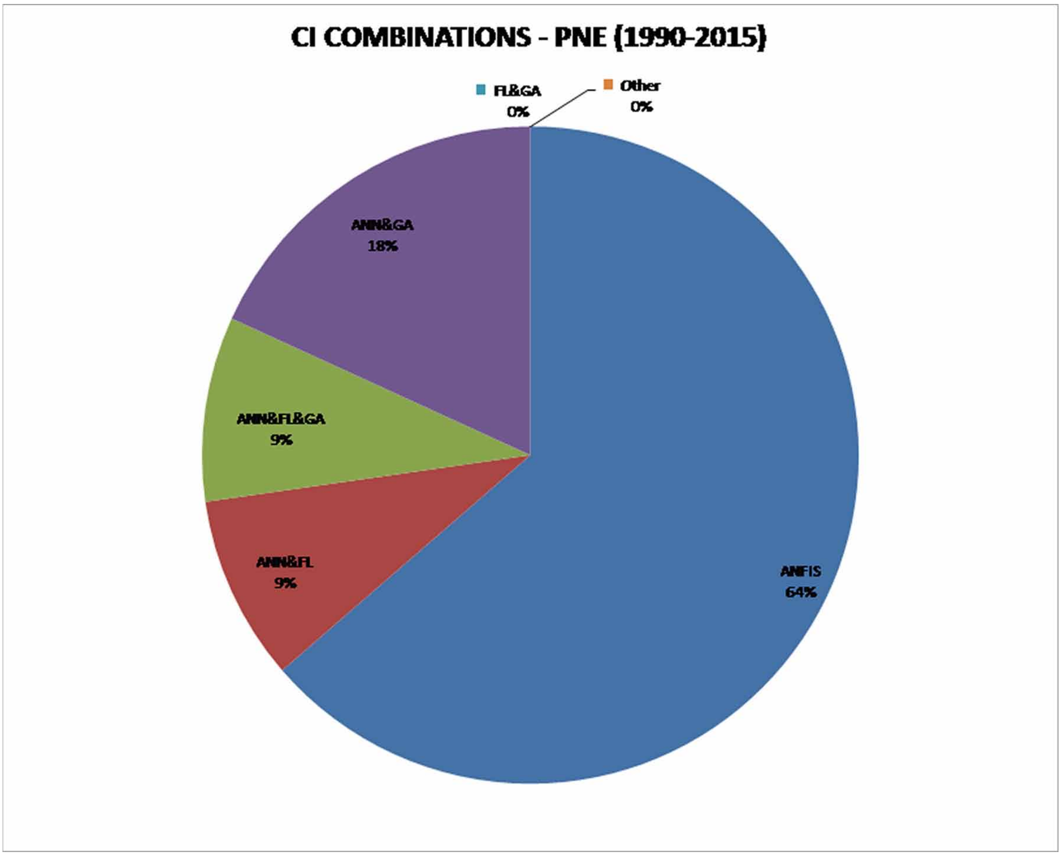


Figure 12c. Yearly percentage (% over the period 1990-2015) of publications involving CI combinations-focused publications grouped by publication medium

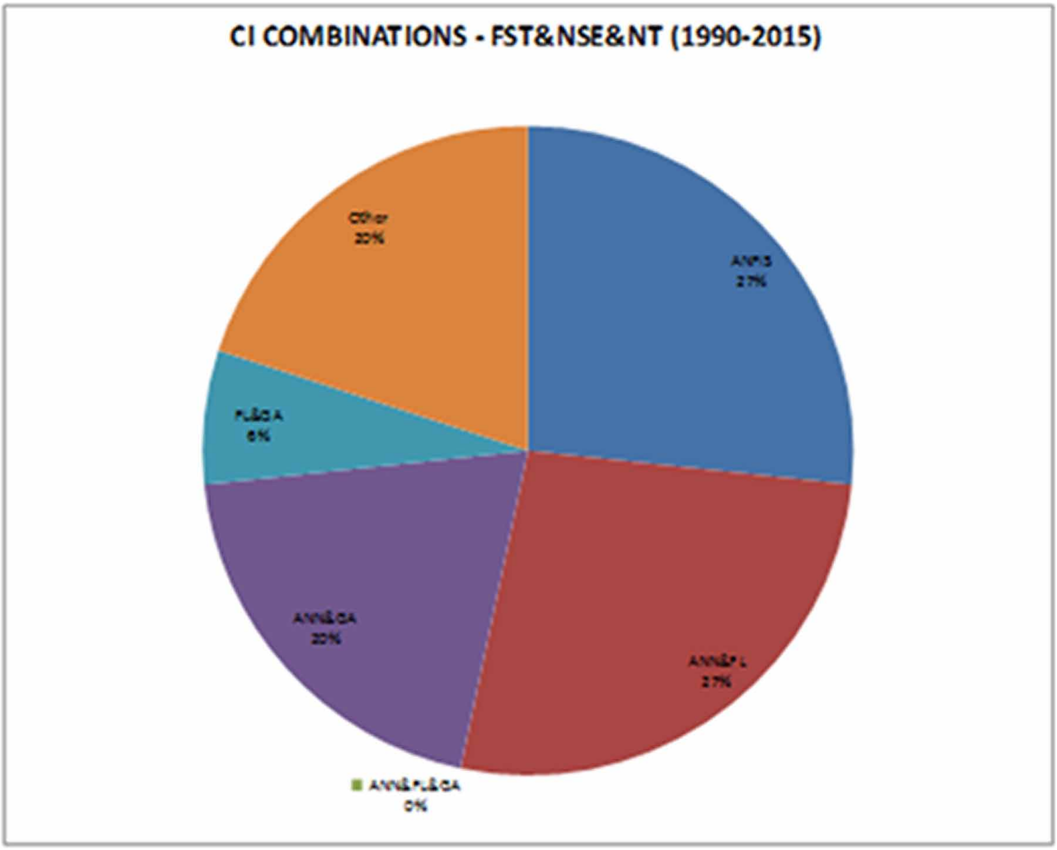


Figure 12d. Yearly percentage (% over the period 1990-2015) of publications involving CI combinations-focused publications grouped by publication medium

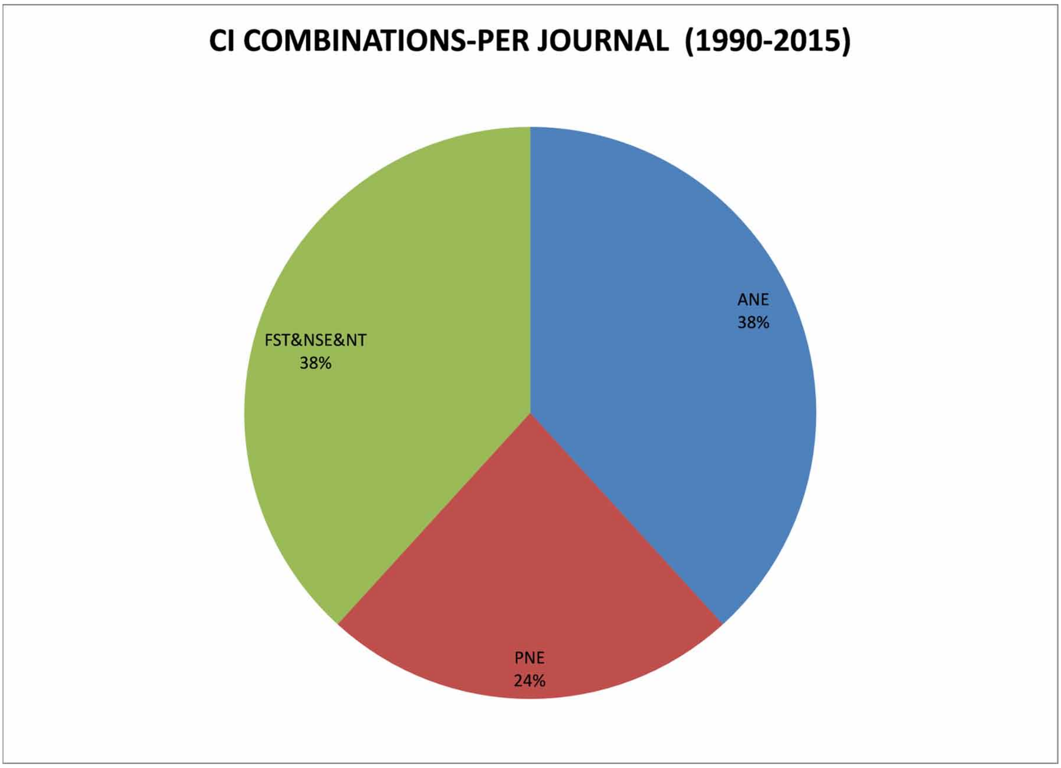


Figure 13a. Yearly percentage (% over the period 1990-2015) of CI combinations-focused publications per key - issue grouped by publication medium

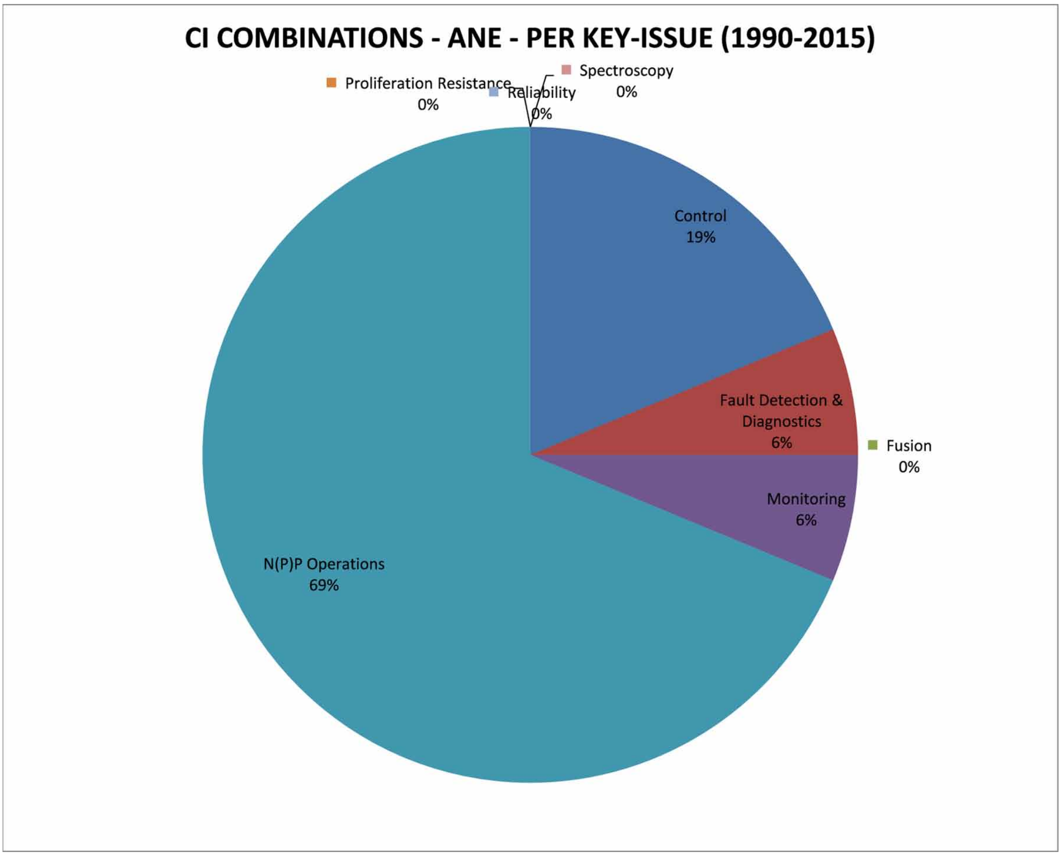


Figure 13b. Yearly percentage (% over the period 1990-2015) of CI combinations-focused publications per key - issue grouped by publication medium

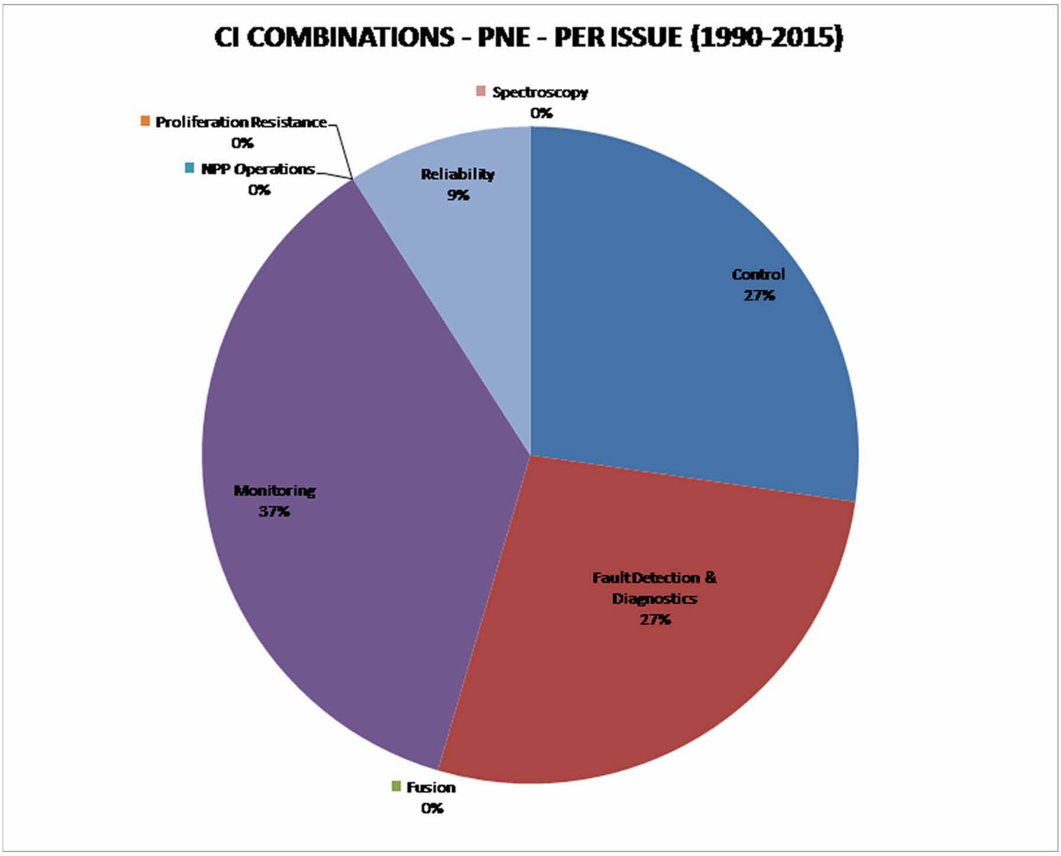


Figure 13c. Yearly percentage (% over the period 1990-2015) of CI combinations-focused publications per key - issue grouped by publication medium

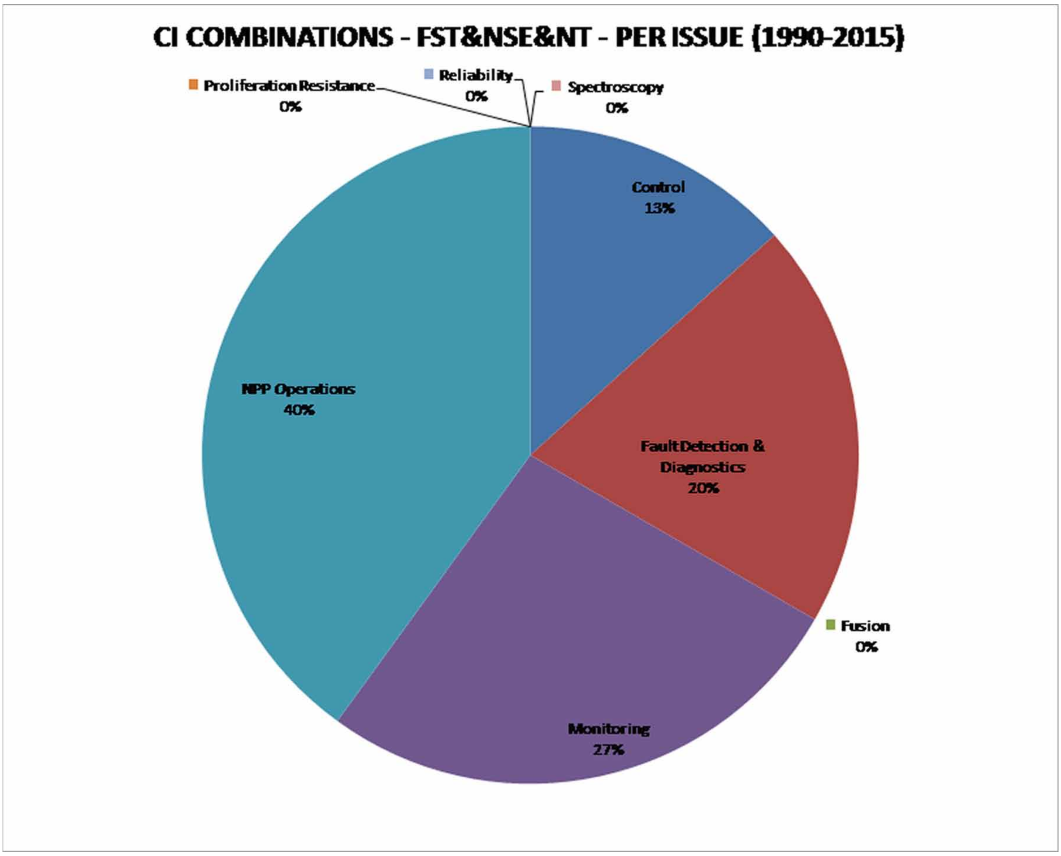
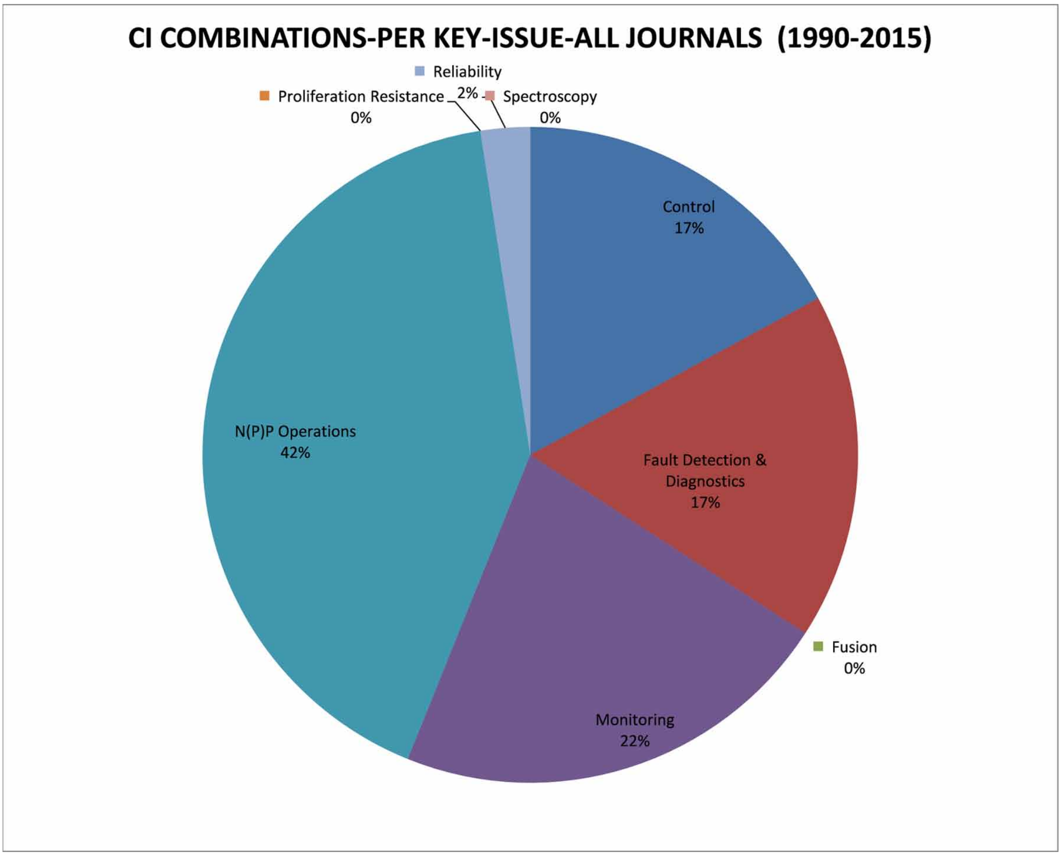


Figure 13d. Yearly percentage (% over the period 1990-2015) of CI combinations-focused publications per key - issue grouped by publication medium



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