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Status of research and development of learning-based approaches in nuclear science and engineering: A review

Mario Gomez-Fernandez[a,d,*], Kathryn Higley[a], Akira Tokuhiro[c], Kent Welter[d], Weng-Keen Wong[b], Haori Yang[a]

[a] *School of Nuclear Science and Engineering, Oregon State University, 100 Radiation Center, Corvallis, OR 97330, United States*
[b] *Electrical Engineering and Computer Science, Oregon State University, 1148 Kelley Engineering Center, Corvallis, OR 97330, United States*
[c] *Energy Systems and Nuclear Science Research Centre, University of Ontario Institute of Technology, Room 4036, 2000 Simcoe Street North Oshawa, ON L1H 7K4, Canada*
[d] *NuScale Power, LLC, 1100 NE Circle Boulevard, Suite 200, Corvallis, OR 97330, United States*

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ABSTRACT

Nuclear technology industries have increased their interest in using data-driven methods to improve safety, reliability, and availability of assets. To do so, it is important to understand the fundamentals between the disciplines to effectively develop and deploy such systems. This survey presents an overview of the fundamentals of artificial intelligence and the state of development of learning-based methods in nuclear science and engineering to identify the risks and opportunities of applying such methods to nuclear applications. This paper focuses on applications related to three key subareas related to safety and decision-making. These are reactor health and monitoring, radiation detection, and optimization. The principles of learning-based methods in these applications are explained and recent studies are explored. Furthermore, as these methods have become more practical during the past decade, it is foreseen that the popularity of learning-based methods in nuclear science and technology will increase; consequently, understanding the benefits and barriers of implementing such methodologies can help create better research plans, and identify project risks and opportunities.

1. Introduction

Over the past decades, many industries have integrated information technologies to support the design and innovation of products and services. While the field of nuclear science and engineering is not known as a highly innovative industry, there has been increasing interest in modernizing the instrumentation in existing and new nuclear reactor technologies (Arndt, 2015) as well as emergent technologies, such as nuclear robotics. The International Atomic Energy Agency (IAEA) has suggested that it *"is necessary to address obsolescence issues, to introduce new beneficial functionality, and to improve overall performance of the plant and staff"* (IAEA-TECDOC-1389, 2004) and to *"enhance and detect subtle variation that could remain unnoticed"* (IAEA-TECDOC-1363, 2003), including the use of artificial intelligence (AI) (IAEA-TECDOC-812, 1995) to support decisions. For instance, in nuclear power plants (NPP) there are approximately 1,200 different alarms for a 3-loop pressurized water reactor (PWR).

In the early days, the field of AI focused on solving problems that were intellectually difficult for humans and problems that could be easily described by simple mathematical rules (LeCun et al., 2015), such as chess. Unfortunately, for tasks in uncertain real-world environments, the development of a set of rules is not practical and becomes infeasible. The subfield of AI, known as machine learning, has the particular characteristic of deriving relationships or set of rules from data, which allows machines to solve more complex problems and deal with uncertainty. Subsequently, its application in engineering as a fast-estimator tool or fast optimization has become an area of research. In the nuclear industry, the interest in developing a computer-aided system to reduce information load in operations tasks has been at the forefront since the 1980s (Buettner, 1985), and in radionuclide detection since the 1990s (Olmos et al., 1991). While many applications of learning-based methods have been proposed, understanding both the potential benefits and challenges that arise from these methods will help individuals to better formulate the problem and collect representative data for a robust implementation.

While the field of AI has seen remarkable achievements over the

* Corresponding author at: School of Nuclear Science and Engineering, Oregon State University, 100 Radiation Center, Corvallis, OR 97330, United States.
E-mail addresses: gomezfem@oregonstate.edu (M. Gomez-Fernandez), Kathryn.Higley@oregonstate.edu (K. Higley), Akira.Tokuhiro@uoit.ca (A. Tokuhiro), kwelter@nuscalepower.com (K. Welter), wong@eecs.oregonstate.edu (W.-K. Wong), Haori.Yang@oregonstate.edu (H. Yang).

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past decade, robustness and ethics in AI is of increasingly concern to the scientific community because of emerging applications of AI in high-stakes applications (Dietterich, 2017), such as surgical assistants (Shademan et al., 2016), autonomous driving (Campbell et al., 2010), power grid stability (Gopakumar et al., 2014), or autonomous weaponry (Arkin, 2009), because of the possible risk imposed to humans lives. Therefore, the purpose of this paper is to: (1) provide an introduction to the fundamentals of artificial intelligence (AI), (2) explore the evolution of different technologies and their integration and challenges within the nuclear science domain, and (3) provide recommendations for more robust implementation in academia and beyond. Furthermore, due to the nature of the paper, more emphasis is placed on concepts and scope of methods while the technical details are left to the references. By providing the reader with this review, it will ease the researcher to better allocate resources and investigative capabilities for future studies.

The reminder of this paper is organized as follow. Section 2 provides a brief overview of the field of artificial intelligence and explores some of the concepts and historical achievements of machine learning methods, particularly neural networks, as they are widely applied in the nuclear domain. Section 3 presents an overview of different applications of machine learning in the nuclear and radiological engineering domain, focusing on identifying the potential benefits and challenges in this specific area. Section 4 discusses and provides suggestions on further research, as well as some of the challenges for a successful deployment of such methods in the nuclear industry. Finally, Section 5 provides a summary, conclusion, and recommendations.

2. Fundamentals of artificial intelligence

The literature on the subject of artificial intelligence (AI) is rather vast and can be overwhelming for non-AI researchers. To better understand the advances in the field, however, it is important to understand the fundamentals as they will guide nuclear and radiological scientists and engineers to better define the objectives for a successful and robust implementation. As one of the newer fields in science and engineering, the term artificial intelligence was coined in the mid-50s at the Dartmouth Summer Research Project on AI. Historically, four schools of thought have been followed as noted by (Russell and Norvig, 2010):

- Think Humanly: the philosophy of fundamentally understanding how humans think (e.g., human reasoning)
- Act Humanly: the philosophy of making machines perform tasks than can be perceived as performed by a human (e.g., Turing, 1950)
- Think Rationally: governed by the field of logic or laws of thought, where problems are described and solved in a logical manner (e.g., solving a problem using principles vs practice)
- Act Rationally: the philosophy of achieving the best/expected outcome, based on the exogenous and endogenous factors over time

These four schools of thought have formed the basis of the overall goal of AI of: building machines that can learn and think like people. Nonetheless, early ambitions diminished over time as the magnitude, difficulty, and lack of understanding of human reasoning was acknowledged (Brooks, 1991). Thus, it is practical to use reductionism by isolating specific aspects that comprise AI. As one of the most important papers in the history of AI, which the authors highly encourage reading, “Steps Towards Artificial Intelligence” (Minsky, 1961) notes five major subfields that fundamentally constitute the AI domain: planning, pattern recognition, credit assignment, and inference; each focusing in solving a different type of problem. *The search problem:* given a well-defined problem, a computer must have ways to find a solution other than an exhaustive search. *The planning problem:* given a complex problem where limitations exists (e.g., time, cost, constraints, and multiple solutions are possible), a machine must have ways to select only a few for full analysis. *The pattern recognition problem*: given a problem, a machine must classify it based on extracting features that are invariant to common distortion into the problem’s different categories. *The credit assignment problem:* uses the analogy of reinforcement to encourage desired behavior, through which a system *“learns”* by stimulation via reward. *The inductive inference problem:* given a specific domain; a machine must have methods that can be used to construct a general statement based on unrecorded information.

Following the combination of these concepts, AI is focused on solving four fundamental problems (Feigenbaum, 1963) to try to model human traits:

1. General problem-solver: modeling *“reasoning”* by modeling the human cognitive process.
2. Game-playing machine: modeling *“strategy”* through strategy games.
3. Question and answering machines: modeling *“comprehension”* through natural language and text.
4. Other applications: modeling *“decision making”* through heuristics, combinatorial, and searching problems.

Subsequently, when a machine is able to answer all fundamental question, then it can be considered to be *“intelligent”*. The latter has been an ongoing debate (Brooks, 1991) and it is beyond the scope of this study. Nevertheless, within the last decade AI systems have been able to play Jeopardy, recognize objects in photos, describe the photos, and recognize your voice and commands in a ‘human-like’ way. Before discussing implementations in nuclear science, let us present the most popular machine learning methods that have and continue to be used for pattern recognition problems.

2.1. Popular machine learning methods

There are several AI methods that can be encountered in the literature, the ‘old-fashioned AI’ (Nilsson, 1980), more modern AI (Russell and Norvig, 2010), and machine learning methods (Bobin et al., 2016; Mitchell, 1997; Murphy, 2012), each having its own strengths and weaknesses. Generally, most machine learning methods try to find an empirical model f that learns from a training data matrix $D \in R^{n\times d}$ obtained from a system, where d is the number of concerned variables and n is the number of training data samples. Machine learning combines the pattern-recognition, credit assignment, and inductive inference problem, where in supervised learning, the updates aim to reduce an error and improve the algorithm’s pattern recognition capabilities by modifying parameters, and for unsupervised learning, the updates work toward matching an expected value based on the presented data (Lake et al., 2016). There are five popular algorithms that can be found in nuclear and radiological science applications; these are decision trees (DT), artificial neural networks (ANNs), nearest neighbor (NN), support vector machine (SVM), and Naïve Bayes (NB), because of their flexibility for pattern recognition problems, see Table 1. Two more are also presented, evolutionary algorithms (EA) and fuzzy logic, as they are found in nuclear- and radiological-related problems as standalone algorithms or in combination with neural

Table 1
Sensitivity evaluation of popular machine learning methods.

Criterion	DT	ANNs	NN	SVM	NB
Mixed data	yes	no	no	no	yes
Missing Values	yes	no	some	no	yes
Outlier	yes	yes	yes	yes	no
Monotone transformations	yes	some	no	yes	no
Data dimensionality	yes	yes	no	no	yes
Irrelevant inputs	some	no	no	yes	no
Interpretable	yes	no	no	yes	yes

networks (i.e., neuro-fuzzy or neuro-evolutionary), in some of the literature.

1.Decision trees are some of the simplest, yet powerful, methods in machine learning and work by partitioning the input space into local simple models in each of the resulting regions. While many optimal partition strategies exist, the most commonly used are based on the GINI index (see CART Breiman et al., 1984), entropy, or information gain (see C4.5 and ID3 Quinlan, 1993; Quinlan, 1986).
2.Artificial neural networks are some of many biologically-inspired techniques that enables a computer to learn from observational data. It is inspired by the biological structure of the brain, where the artificial counterpart reproduces a similar functionality (McCulloch and Pitts, 1943). They work by presenting data to the network via the 'input layer,' which communicates to one or more 'hidden layers' where the processing is done via a system of weighted 'connections.' The development and success of the error back-propagation algorithms, gives the network the ability to use a loss function to find a learning rule that decides under which circumstances the weighted connections need to be modified such that the desired value and the actual output value are close (Rumelhart et al., 1986). ANNs are the dominant learning-based algorithm used in nuclear and radiological science (Ma and Jiang, 2011) because of their ability to deal with nonlinear, inconsistent, and noisy data (Tsoukalas and Uhrig, 1996; Adali et al., 1950).
3.k-Nearest Neighbor is an intuitive classification technique that classifies a data instance according to the majority class of its k nearest neighbors. This algorithm requires a distance metric such as Euclidean distance.
4.Support vector machine is a powerful non-parametric method whose principal idea is to construct a decision boundary that maximizes the distance to example points, referred to as maximum margin separator. Furthermore, SVMs have the ability to embed the data into a higher dimensional space using the original set. By transforming the data into a higher dimensional space, a linear separator is found. This linear separator is nonlinear when transformed back into the original space. This is the so-called *kernel trick*. For further details see Cortes et al. (1995), Schölkopf et al. (1999) and Wang et al. (2017)
5.Naïve Bayes is formulated based on Bayes theorem $P(y|x) = \frac{P(x\mid y)P(y)}{P(x)}$, where the prior probability ($P(y)$) is estimated using the training set, and the class-conditional probability $P(x|y)$ is estimated assuming that the input variables are conditionally independent (i.e., $P(y|x) = \frac{P(y)\prod_{i=1}^{N}P(x_i\mid y)}{P(x)}$).
6.Evolutionary learning techniques are popular because of their nature-inspired concept of simulating the evolutionary process. These holistic approaches do not guarantee a best solution; however, they generate or approximate a good enough (local optimum) solution to complex problems in a reasonable amount of time. Generally, the central common feature of all evolutionary methods is that they start off with an arbitrary initial solution, iteratively produce new solutions by a (simple) rule, evaluate the newly generated solutions by a penalty or fitness function, and report the best solution found during the search process. Presumably the goal of generating solutions is to create more, and varied, solution conjectures to enhance diversity and quality. For further details see Bäck (1996), Cortes et al. (1995) and Freitas (2003).
7.Fuzzy logic is a technique derived from the so-called principle of incompatibility (Zadeh, 1973) which correlates imprecision and uncertainty to the complexity of a complex system. Introduced in 1965 (Zadeh, 1965), fuzzy set theory and fuzzy logic revolves around the idea that given two sets, an object can belong to a set with a degree of membership. This deviates from the classical set theory and classical logic where an object either belongs to one set or not. Fuzzy logic approaches are efficient when applied in fields where imprecision and uncertainty is high and are less efficient when precision is apparent (Ponce-Cruz and Ramírez-Figueroa, 2004). For details on the evolution of fuzzy logic see Zadeh (2015)

2.2. Beyond classical ANNs

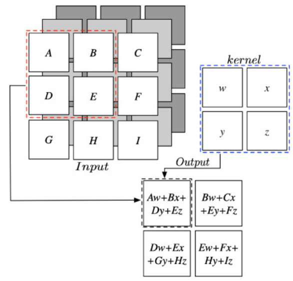
In the new millennium, multi-layered ANNs have demonstrated remarkable performance when data is plentiful because they have outperformed other alternative machine learning methods (e.g., SVM) through improved representation learning via many hidden layers and improved optimization algorithms that facilitate training. ANNs have been mathematically substantiated to be universal function approximators (Cybenko, 1989; Hornik et al., 1989; Leshno et al., 1993) (i.e., according to the universal approximation theorem), there exists a neural network with at least one hidden layer with a finite number of units that can approximate any function at any desired degree of accuracy. Additionally, training speed also saw a breakthrough with the utilization of graphical processing units (GPUs), which excel at fast matrix and vector multiplications required not only for image processing but can also be used for ANN training. GPU hardware reported an increase in speed by a factor of 20 (Oh and Jung, 2004) or more based on the specifications, and better computational scalability (Strigl et al., 2010) than central processing units (CPUs). Deep learning (DL) models have rapidly evolved to become the state-of-the-art technology in machine learning tasks such as object recognition, speech recognition, adversarial games, and controls. The two most popular deep learning structures are *convolutional neural networks* for object detection in images and *recurrent neural networks* and *Long Short Term Memory* for sequential information with time dependencies. Although these require higher levels of understanding to appropriately tune them, the application of these structures has been rather limited in nuclear sciences, but some examples are detecting steel cracks underwater using video (Chen and Jahanshahi, 2018) or isotope detection (Kamuda et al., 2019) using convolutional structures.

2.2.1. Convolutional neural networks

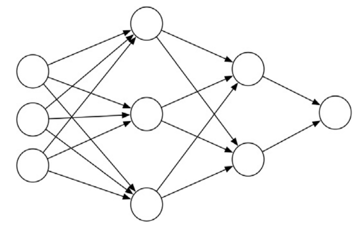
Convolutional neural networks, more commonly known as CNNs or ConvNets, were firstly introduced in (Fukushima, 1979; Fukushima, 1980; Fukushima, 2013) by means of mimicking the vision process of mammals, and later implemented for handwritten number recognition (LeCun et al., 1989). Currently, CNNs are the dominant structure for object recognition tasks and it can be comparable to human-level performance (He et al., 2015; Russakovsky et al., 2015; Szegedy et al., 2014). The novelty of the approach was the use of convolution layers to significantly reduce the number of parameters that needed to be optimized, as shown in Fig. 1a, which both reduces the memory required and increases the model efficiency. The convolution layer consist of three different stages: convolution, activation, and pooling. First, a convolution is a mathematical operation of two functions of real value arguments that form a new function (Goodfellow et al., 2016). Secondly, each entry is then transformed by a nonlinear activation function to extract features. At the pooling stage, the pooling function replaces the output of the network with a statistical summary of the nearby outputs. The key concept from this stage, is to make the representation invariant to small transformations of the inputs. Thus, after the feature extraction stage the $m \times n$ image is divided into a $m \times n$ disjoint and take the max (or other function) feature activation over these regions to obtain the *"convolved features"* that can then be used for classification.

2.2.2. Recurrent neural networks

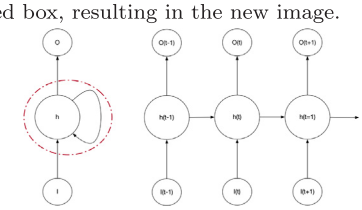
Recurrent neural networks (RNNs) have been the preferred choice for tackling memory tasks with time dependencies. However, when long-time dependencies are required to be learned, RNNs suffer from the vanishing gradient problem (Hochreiter, 1998), for which memory structures have been proposed in the form of gated units. Gated recurrent neural networks are based on the idea of hybrid-designed gates



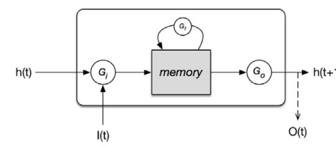
(a) 2-D convolution representation, where the blue dotted box represents the filter or kernel that is multiplied by the red dotted box, resulting in the new image.



(b) A typical feedforward neural network representation or two hidden layer and one output layer.



(c) A recurrent network structure representation with the unfolded equivalent. The red dotted line represents the section where more elaborated units are placed, such as the shown in 1d.



(d) Conceptual visualization of gated units, where G_i is the input gate, G_o is the output gate, and G_f is the forget gate.

Fig. 1. Popular deep learning structures.

that create pathways through time whose derivatives neither vanish nor explode (Goodfellow et al., 2016). This is achieved by using three types of control gates: the write control that determines the input to the memory state (with linear activation), the forget gate that controls how much of the stored memory value is transferred to the next time step, and the output gate which regulates the output of the memory cell. The most popular gated type units used are the gated recurrent unit (GRU) (Cho et al., 2014) and the Long Short Term Memory(LSTM) (Greff et al., 2015), and these are regarded as the state-of-the-art for sequential data such as speech recognition and translation (Sutskever et al., 2014).

2.3. Comparison of popular algorithms

While it is unrealistic to expect that the data collection or generation is going to be perfect, data availability is one of the major factors that determines which method is suitable for a successful application. A selection criteria is presented in Table 1 (Dietterich, 2005; Tan et al., 2005) with the following criteria explanations:

- Mixed data: the ability to handle different types of data (i.e., continuous, discrete, etc.)
- Missing Values: sensitivity to unrecorded data
- Irrelevant inputs: sensitivity to values that do not contain relevant information to the application
- Outlier: robust to unusual or inconsistent values
- Data dimensionality: ability to handle increasing features in data sets
- Monotonic transformations: sensitivity to monotonic transformations
- Interpretable: ability to understand the rationale behind the decision/classification of the algorithm (Doshi-Velez and Kim, 2017)

3. Intelligence augmentation: a nuclear and radiological challenge

The civil uses of nuclear technology have a number of different applications with various benefits to the general public. Medical applications include the use of nuclear materials to diagnose, monitor, and treat many different human conditions; industrial applications are numerous and are characterized by being non-intrusive including sterilization, radiography, smoke detectors, and food safety among others; academic applications include the use of nuclear material for laboratory practices, and research and development; and energy applications include to produce electricity, heat water, and work in conjunction with other energy sources. While it is common to characterize physical systems employing first principles, which can be very accurate when the underlying laws are well known, empirical methods can be used to develop approximate mathematical models when the laws are not well understood (de Oliveira et al., 2000), which, if used correctly, can be very useful.

This section presents the performance and flexibility or machine learning methods in nuclear technologies, with a focus on nuclear reactor health monitoring, gamma spectroscopy and optimization, and their support to both technical and economic objectives shown in Table 2; ultimately, enhancing safety, reliability, and availability of the equipment. The collective problems in this section are of different types: (1) regression refers to the prediction of continuous values, (2) classification to the prediction of a category or class, or (3) combinatorial and exploratory. In nuclear engineering, researchers have identified the potential use of pattern recognition in various tasks in nuclear reactors (Uhrig et al., 1999; Uhrig et al., 1998; I.N.E.S. NP-T-1.2, 2008; I.N.E.S. NP-T-1.1, 2008). In radiation detection, research takes advantage not only of the pattern recognition to analyze the reactor detectors' signals for anomalies, but also to analyze and categorize gamma and neutron spectrums for transportation, security, and environmental monitoring. Lastly, optimization applications use available data for the discovery of more, and varied, solutions in a timely manner.

Table 2
Nuclear Science Objectives.

Technical	Economical
• Reduce radiation exposure to personnel • Enhance equipment reliability • Avoid actuation of safety systems • Assist with correct and timely decision making • Enhance safety margins	• Optimize the maintenance schedule • Improve plant availability • Avoid escalation of minor problems into major event • Support power uprate and life extension

3.1. Plants health and management approaches

In nuclear power plants (NPPs), there are a wide variety of tasks that have been studied using learning-based methods, particularly the development of neural network structures for parameters prediction and classification using sensor data to perform monitoring, diagnosis, prognosis, controls, planning, and other tasks that can benefit from pattern recognition. Degradation, ageing, and transients can happen over a short or long period of time; thus, it is feasible to extract a unique set of patterns or fingerprints for the operators to perform a root cause analysis in a timely manner. The primary goal of such applications is to provide a quick and accurate insight such that additional time can help derive the optimal procedure/strategy to be implemented to correct the situation via artificial anticipators or fast first estimation tools, therefore increasing the safety of the plant and components.

In NPPs, learning-based methods have been studied for instrument calibration monitoring, equipment monitoring, reactor core monitoring, loose part monitoring, transient identification, reactor controls, and others. The task of monitoring and diagnosis systems consists of detecting the departure of a process from normal conditions to characterize the new process/state based on temporal trends (Denœux et al., 1997). Conventionally, a fault threshold level for each plant parameter is set and an alarm is given when the signal exceeds the threshold level (i.e., if-then rules derived from model-based approaches Frank, 1990; Isermann, 1984; Basseville, 1988). However, minor abnormal conditions may not be detectable until they reach a critical threshold (Boring et al., 2015; Ulrich et al., 2015), which is where computer-aided systems can prove to be worthwhile. Plant health and management capabilities are not unique to the nuclear industry, as other complex engineered systems are also interested in such features (Tan et al., 2016; Schlechtingen et al., 2013; Mirowski et al., 2014; Shahid et al., 2012; Ge et al., 2008), which translates to better performance and help conserve the asset in optimal conditions. The economic impact of the development of advanced systems can have a potential savings of $48 billion USD over a 40-year life span of a typical power plant as shown in Chai et al. (2003); roughly $1 billion USD per year, when optimal operation is maintained.

Research in the monitoring domain using simulators and codes has been extensive (Sirola et al., 2012; Fantoni et al., 1996; Santosh et al., 2009; Kim et al., 1992; Subhra et al., 2010; Vinit Tarey et al., 2012; Pinheiro et al., 2019; Nabeshima et al., 1998; Uhrig, 1991; Yang et al., 2018; Boring et al., 2015; Na et al., 2006; Ulrich et al., 2015) because of the potential economic impact. Nevertheless, for the success of intelligent aided systems in the nuclear industry, the use of real or prototypical systems is also encouraged as such systems will be subject to the problem of verification and validation (V&V) (Kim, 1994). Some examples of machine learning studies using real plant information are: the Tennessee Valley Authority Sequoyah NPP (Zhichao and Uhrig, 1992) to determine the variables that affect the heat rate and thermal performance, Watts Bar NPP (Bartlett et al., 1992) for operating status recognition, High Flux Isotope Reactor operated at Oak Ridge National Laboratory (Hines et al., 1996) for sensor calibration systems and sensor fault detection systems, experimental Breeder Reactor (Upadhyaya and Eryurek, 1992), prototypical Small Light Water (Fernandez et al., 2017) for plant wide behaviour analysis, and Narora Atomic Power Station (Vinod et al., 2003) to identify eight particular initiating events. Although there have been some real setting applications, the use of real NPPs information for performance studies has been rather limited due to the highly regulated industry and intellectual property protection concerns (Uhrig et al., 1999; Adali et al., 1950; Wallace et al., 2011).

Other applications where machine learning methods can be encountered are: the prediction of the behavior of systems components such as heat exchangers (Ridluan et al., 2009; Patra et al., Feb. 2010; Wijayasekara et al., 2011; Patra et al., 2012), power peaking factor estimations (Montes et al., 2009; Patra et al., 2012), key safety parameter estimation (Mazrou, 2009; Farshad Faghihi and Seyed, 2011; Calivá et al., July 2018), aging and degradation (Boshers et al., 1993; Agarwal et al., 2015), uncertainty propagation (Krivtchik et al., 1991), severe accidents classification (Na et al., 2004; Ma and Jiang, 2011; Lee and Lee, 2006), functional failures of passive systems (Zio et al., 2010), research reactors (Nasrine Allalou et al., 2016), and more recently crack detection in internal reactor components (Chen and Jahanshahi, 2018). All of these problems are well suited, with the advantage that more data can be generated or made available to researchers.

3.1.1. Flow regime identification

Other related areas to reactor safety is the identification of flow regimes. Several methodologies for flow identification seem to be subjective based on visual observations (Tsoukalas et al., 1997), with some being more objective (Vince and Lahey, 1982; Jones et al., 1975). The use of learning-based methods to predict flow regime identification based on nonintrusive instrumentation has been explored mainly using feed forward neural networks (Lombardi and Mazzola, 1997; Mi et al., 1998; Mi et al., 2001; Sunde et al., 2005; Tambouratzis and 10.1016/j.anucene.2010.02.004, 2009; Tambouratzis et al., 2010; Lee et al., 2008; Crivelaro et al., 2002; Hernandez et al., 2006; Juliá et al., 2008), including some deep learning approaches (Yang et al., 2017; Guo et al., 2016). Proper flow regime identification can accelerate the design analysis and operation of engineering systems as correct hydrodynamic and kinematic mechanism can be modeled. Additionally, nonintrusive techniques can be used for the detection of wears, leakages, or unwanted events while operating.

3.2. Radiation protection

As one of the fundamental pillars of nuclear safety, intelligence augmentation also extends to its application in radiation protection-related tasks. In spectroscopy, the goal is to find a pattern or structure, full peaks in most cases, and differential count rates by analyzing the distribution of counts over a spectrum. Efficient and accurate characterization and identification of radionuclides is of great importance as it can help with illicit transportation of radioactive materials, or contaminants in the field, which are traditionally determined using gamma spectroscopy. There is a wide variety of application for spectroscopy ranging from the analysis of the instrumentation, the spectrum itself, its meaning, and its derived features. Radionuclide identification using learning-based methods based on gamma and neutron spectroscopy is of interest as such approaches do not require templates or peak libraries calculated in advance (Fagan et al., 2012). Moreover, they can help discern subtle patterns in large multivariate data sets to reduce false negatives (Kangas et al., 2008), calibration drifts (Kamuda et al., 2018), data uncertainties (Dragović et al., 2005), and peak overlapping (Baeza et al., 2011; Alizadeh and Ashrafi, 2019). Other applications with limiting research include nuclear stability and decay (Gernoth et al., 1995), SVM for anomaly detection from thermoluminescent dosimeter (TLDs) glow curves (Amit and Datz, 2018), radiation signals encryption (Chatzidakis et al., 2014), radiation therapy (Bibault et al., 2016), among others. However, because of the large use of spectroscopy in the field, the scope of this section will be focused on this particular application. While the interest has been extensive, and many different learning-based algorithms have been used, neural networks are the dominant method.

In gamma spectroscopy, research related to the identification of isotopes for hand-held instrumentation (Kamuda et al., 2019; Keller and Kouzes, 1994) based on ANSI N42.34 standard isotope selection (A.N.S. Institute, 2007), independent isotope classification (Abdel-Aal and Al-Haddad, 1997; Yoshida et al., 2002; Shahabinejad et al., 2018; Bellinger et al., 2015; Chen et al., 2009), mixture of elements (Olmos et al., 1991; Kamuda et al., 2019; Bobin et al., 2016; Abdel-Aal and Al-Haddad, 1997), and specific activity of naturally occurring radioactive materials (NORMs) (Sheinfeld et al., 2017; Medhat, 2012) have been carried out. Similarly, neutron spectroscopy analysis has been a subject of research using Bonner sphere systems (Vega-Carrillo et al., 2006; Ortiz-Rodriguez et al., 2013; Kardan et al., 2003), and neutron dose estimation (Vega-Carrillo et al., 2009) using neural networks have been reported. The identification of radionuclides can also be extended to other specific subfields such as special nuclear materials detection and environmental monitoring where detection is more difficult. In other specific areas such as optimization, one of the key principles of radiation protection, via machine learning approaches can lead to the discovery of solutions that typical deterministic approaches are not able to provide or for which the exploration can be too costly.

3.2.1. Special nuclear material

Illicit nuclear material trafficking is one of the applications where substantial efforts have gone into devising strategies for inspection. The use of gamma spectroscopy is also extended to nonproliferation and nuclear security applications. However, special nuclear material (SNM) identification presents additional challenges, such as data collection time, background level, and attenuation or distorted shielded spectrums, where scientists have applied machine learning methods to improve on such challenges. Clustering methods for radioxenon classification (Sharma et al., 2012), neural networks for shielded plutonium (Aitkenhead et al., 2012), uranium ore compound classification (Ho et al., 2015; Hata et al., 2015), spent fuel pool classification to ease nuclear forensics (Jones and Turner, 2014), and general SNM detection using: fuzzy logic systems (Alamaniotis et al., 2013; Alamaniotis et al., 2009; Alamaniotis et al., 2009; Alamaniotis and Tsoukalas, 2015), evolutionary algorithms (Alamaniotis et al., 2013; Alamaniotis and Jevremovic, 2015), Gaussian process (Alamaniotis et al., 2015), naïve bayes (Dalal and Han, 2010; Sullivan and Stinnett, 2015), are some of the different tasks for which learning-based methods have been considered. The Gamma Detector Response and Analysis Software (GADRAS) (Horne et al., 2014; Klasky et al., 2016) has been used as a training data generator in some of the presented work for both gamma and neutron spectrums.

3.2.2. Environmental monitoring

Environmental monitoring is achieved mainly from the detection of gamma radiation, as it is the most penetrating radiation either natural or anthropogenic. Other situations include the environmental application of gamma spectroscopy for geological, geochemical, and environmental mapping, allowing the interpretation of regional features, such as atmospheric radon levels; human-made contamination around nuclear facilities to determine a baseline for accidental releases; mining and other industrial activities (IAEA-TECDOC-1363, 2003; IIAEA-TECDOC-1017, 1998). However, environmental systems present a particular barrier that their dynamics are complex, nonlinear, and affected by many exogenous stressors; therefore, the development of simulation models, risk mapping, spatial predictions, representative data collection and analysis (Kanevski et al., 2004) are ongoing challenges, where models obtained through empirical data are typically better suited than those from analytical equations (kuo Liu et al., 2014; Hsieh, 2009). Some noticeable studies are, legacy site Ra-226 contamination characterization (Varley et al., 2015) and distribution (Varley et al., 2015); and remediation monitoring (Varley et al., 2016), which can serve as a first estimation tool to provide rapid insights of the activity, depth, and distribution of the contamination. Estimation of an ambient dose rate risk map using various machine learning methods (Yeşilkanat et al., 2017), spatial prediction of fallout at the Chernobyl site (Kanevky et al., 1997), suitability of neural networks for uranium activity ratio in environmental spectra (Einian et al., 2015), and bio-availability and bio-accumulation of NORMs in aquatic species through produced water from the gas and oil industry (Chowdhury et al., 2004; Shakhawat et al., 2006), are some of the areas that have shown promise for the potential benefit of learning based methods. Other technologies such as the Internet of Things (IoT) are also being explored in the field of environmental monitoring (Muniraj et al., 2017; Lin and Liaw, 2015).

3.3. Optimization

Designing and analyzing engineering systems can be a very complex process, of which energy systems are an exceptional example. Optimization can be defined as the *"act of obtaining the best result under the given circumstances"* (Rao, 2009). The highly iterative process in an interdisciplinary environment leads to multiple suboptimal designs or decisions until one is determined to be the best performing one (i.e., meeting the requirements imposed as well as being cost-effective, efficient, reliable, and durable (Arora, 2016)). In practical engineering, optimization problems are expressed as an analytical function that includes decision variables and constraints, such that traditional optimization tools can be used (e.g., first or second order optimization algorithms). However, in some cases analytical formulations are not feasible or too simplistic to capture the complexity, for which nontraditional or modern optimization methods are of particular interest.

In nuclear and radiological engineering, many processes can be optimized by using a well-studied, and justifiable, machine learning method. Bio-inspired methods, such as neural networks, evolutionary algorithms, and particle swarms, among others, are very popular in the optimization domain as their working mechanism allows them to generate more, and varied, solutions to enhance diversity and quality. Combinatorial types of problems can easily take advantage of these methods; for instance, in fuel loading management (Erdoğan et al., 2003; Siegelmann et al., 1997; Faria et al., 2003; Hill et al., 2015; Zameer et al., 2014; Jayalal et al., 2014; Eliasi et al., 2012), optimal maintenance scheduling (Volkanovski and Cizelj, 2014), dry cask loading (Spencer et al., 2018; Spencer et al., 2019; Bartlett, 1992), packing and waste handling (Hopper and Turton, 1998), or dose optimization (Wang et al., 2018; kuo Liu et al., 2014).

3.3.1. Robotics and controls

Although the scope of this paper is on learning based methods, robotics and controls are complementary, as optimization is at the core of control theory and machine learning methods are also being evaluated (Zhang et al., 2018). The desire to provide autonomy (i.e., ability for self-governance in the performance of functions (Antsaklis et al., 1991)) to machines has been one of the fundamentals of the field of artificial intelligence as it can eliminate or reduce human roles from low level tasks. Optimization and controls are conceptually different, where the goal of controls is to produce a desired output given feedback from the systems controllers (Arora, 2016), (i.e., the output is known). Robotics in the nuclear industry can be beneficial by substantially reducing the time that an individual has to spend in a radiation area and remotely handling material that is considered hazardous, or when the conditions of the environment or structural integrity are unknown. For instance, (Wood et al., 2017) identifies three key areas where autonomous controls can be beneficial: (1) detection and progression limitation of off-normal events, (2) detection and response to degraded or failure conditions (Lee et al., 2018), and lastly, (3) potentially unattended operation with limited human interaction (Uhrig et al., 2003). Others include, reactor temperature or power control (Ku et al., 1991; Ku et al., 1992; Arab-Alibeik and Setayeshi, 2005; Na et al., 2006), coordinated control strategies development using fuzzy logic and neural networks in a multi-unit small modular reactor (Zhang et al., 2019; Zhao et al., 2015), inspection (Yim et al., 2013), hazardous material search and radiation mapping using robots(Zakaria et al., 2016; Sinclair et al., 2016; Tokuhiro et al., 2004), and computer vision for radwaste management (Shaukat et al., 2016). Robotics and controls present some particular challenges as they require special design considerations, material selection, operational constraints, processes knowledge, etc. With high-stake controls, it is of paramount importance that the probability of taking or advising the wrong solution path is minimal, which is part of the *robust artificial intelligence* presented in recent years

(Dietterich, 2017).[1]

3.4. Suitability of popular algorithms in nuclear and radiological problems

This section presents a general analysis based on the commonly collected data for each of the different applications and is summarized in Table 3. Please note that more than one algorithm among the popular algorithms can be applied for a specific task, which is also reported in the literature. Other factors such as training speeds/cost, accuracy, model complexity, interpretability, etc., become part of the selection process and are beyond the scope of this review. Table 1, along with literature (i.e., Section 3), is used to provide an overall assessment of the suitability of the algorithms that have been presented.

Moreover, it is worth noting that most, if not all, existing engineered systems of relevance here consists of the human, measurement of physical phenomena, purposeful design of small to large engineered devices and systems (D&S) and other than unanticipated events, operation of devices and systems as designed, constructed and intended. On the basis thereof, both phenomena and function of D&S many times have been created with inherent *complexity* (i.e., with multiple variables/parameters not only interacting within the D&S but via human–machine interaction). The current state of understanding of complexity is limited and rudimentary not only because those who acknowledge complexity are scattered across disciplines, but there is no emerging consensus on characterizing it. The emerging application of learning-based approaches, across the sub-disciplines and applications noted herein is an attempt to characterize the complex interactions of phenomena and D&S via an algorithmic approach that relies on coded sampling of limited channels/streams of data generated by measure or functional 'gauges' of the D&S. What is evident in the applications described here is that phenomena and D&S with say approximately 10–50 variables and parameters approximately defined complexity and that characterization of such a problem is limited to non-existent.

Further, learning-based methods of relevance and complexity level herein implied are largely known or recognized as substantiating the bulk of any characteristic distribution of recurring phenomena or function. In other words, these methods do not work well for outliers. Characterizing rare occurrences, such as "black swan" events, are not well-suited for these methods. Thus, as noted by Agrawal et al. (2018) and Tokuhiro (2019), learning-based methods are able to decipher many familiar, coded 'if-then-when' instances at a systematic level as inspected and then predict the likely next occurrence. Therefore, at this time, prescriptive and systematic approaches and methods to complexity, other than accessible cases of applicability as cited here, do not yet exist.

4. Discussion and suggestions

In many industries, the rapid growth of information is creating a dependence and reliance on advanced algorithms to analyze and make decisions, or partial decisions, gradually reducing human involvement. Unlike the nuclear industry, nonnuclear power systems have made digital upgrades to their systems, whose lessons learned can be an advantage for more effective modernization (IAEA-TECDOC-1389, 2004). While automating and modernizing technology is part of its evolution (Sheridan, 2002) notes that underloading the mind can be just as harmful as overloading because new issues arise not only by the levels of automation defined for the domain, but also the result from the interface between the user and automation (OHara and Higgins, 2010). Failure to acknowledge the challenges can lead to the following: misuse or the over-reliance on automation; disuse or the under-utilization of automation; and abuse or inappropriate application of automation (Parasuraman and Riley, 1997). Thus, fostering experts' understanding of the benefits of developing learning-based solutions can help avoid potential issues. Moreover, a lack of proper evaluation method has previously been identified in Reich and Barai (1999), resulting in additional challenges and an impediment to the progress and improvement in research and practice in the application of learning-based methods in engineering.

4.1. Ethics

The aspiration to apply and deploy intelligent systems to improve processes is a co-evolution between developers, users, and technology. Unfortunately, such human-machine symbiosis is coupled with ethical issues, which are not always anticipated by developers or the common users. While data and algorithms are ethically neutral (i.e., they don't have a built-in perspective on what is right/wrong or good/bad), the use of data and learning-based algorithms can represent a risk (e.g. trusting black box models). Moor (2006) provides a philosophical discussion of how developers tend to evaluate the performance of the tools based on accomplishing what they were designed for, and after the technology matures, these norms become of second nature (i.e., ethics derived from their human developers). Other prominent ethical issues in the AI domain that are inherently carried over to other domains are: undesirable uses of AI (Schulzke, 2013), loss of accountability (Beiker, 2012; Floridi and Taddeo, 2016), and machine ethics (Anderson et al., 2005). All of these constitute an active, and rapidly evolving, area of research that continues as the adoption of AI methods increases.

Because AI methods have not been extensively used, and AI-based autonomy is still in early research stage in nuclear science and engineering, ethical issues are not commonly mentioned. Based on the state of the technology, the goal of intelligent systems in nuclear sciences must be to inform and provide users with the appropriate inputs to *formulate, conform, and perform* the most effective actions, and *not* the replacement of any human input. A human counterpart has the expertise to ensure that trade-offs are fully understood before taking proper decisions, while taking advantage of the superior data processing from computers. Thus, learning-based systems should be a supplement to, rather than a substitute for, traditional methods to enhance decision making. This holistic approach should serve as a guide to the development of robust intelligent augmentation systems through the most effective implementation of learning algorithms toward the desired task, heeding the different objectives shown in Table 2, Table 1 and Section 2. Further consideration beyond the technological advantages and ethical issues are legal and social implications and the development of guidelines and standards (with a recent publication being OECD, 2019).

4.2. Collaborative and open access research

As information technologies continue to advance, so is the way research is being conducted and shared; particularly in the fields of AI/ML. The concept of FAIR (Findability, Accessibility, Interoperability, and Reusability) (Wilkinson et al., 2016) is now a reality that all researchers must consider. Open platforms, such as GitHub Inc., allow research to be shared such that reproducing others' work is simple, and improvements on the current state of the research can be made. Thus, increasing FAIR and focusing on new ideas will avoid unnecessary time expenditure in reproducing results or duplicating research. Moving the research process into a more collaborative and inclusive process will encourage more discussion and interaction with other peers, companies, and developers, during (and after) the research cycle. This process, in principle, increases the quality of the contributions made and accelerates innovation. While sharing information is one way of facilitating research, information technologies include other research enhancers such as the Internet of Things/IoT (see Section 3.2.2) and cloud

[1] For a more detailed review on nuclear robotics, see Bogue (2011), and radiation effects on electronics, see Kuwahara et al. (Dec 2012) and Messenger and Ash (1986).

Table 3
Algorithm selection scheme for nuclear and radiological data criteria.

Plant health and management: Data collected for this application consist mainly of NPP's sensor data or synthetic data (simulators or codes), which mainly represents continuous data collected over a long period of time from different sensors, i.e., large datasets. Noise has to be considered when applied to NPP data collection	
DT	Suitable; better suited for categorical features, larger trees are hard to interpret, small changes in input data can result in low accuracy (misclassification).
ANNs	Suitable; require hyperparameter search (time consuming), data-hungry, not interpretable.
NN	Unsuitable; Very sensitive to the definition of neighborhood, does not perform well in high dimensions, computationally expensive for large data sets.
SVM	Somewhat suitable; requires tuning hyperparameters (time consuming), not suitable for extremely large data sets.
NB	Unsuitable, conditional independence assumptions between variables are usually not suitable for monitoring applications operating on time series
Flow Regime Identification: Data used in flow regime identification has mainly consisted of visual representation for both vertical and horizontal flow regimes. This data includes variations in bubbles shapes, locations, deformations, diameters, etc.	
DT	Unsuitable; it requires very large trees, sensitive to input variations.
ANNs	Suitable; mainly CNNs, same requirements as above.
NN	Unsuitable; does not perform well for high dimensional data.
SVM	Somewhat suitable; sensitive to variations, transitions between regimes will affect its performance (i.e., hard to know which kernel function works best).
NB	Suitable; feature engineering is required, conditional independence assumption may be too strong.
Spectrometry: Data collected for this application is measured information and synthetic information. Typically the raw data is uses, i.e., all channels with no preprocessing	
DT	Somewhat suitable; small changes in input data can result in misclassification (e.g., decalibrated samples).
ANNs	Suitable; RNNs should be considered for temporal spectrometry. Same challenges as above.
NN	Somewhat suitable if the nuclides of interest are strong gamma emitters and peaks do not overlap; it does not scale well, other algorithms might achieve better classification performance.
SVM	Suitable if the data set is not large (e.g., number of channels matter); irrelevant information can result in misclassification (e.g., background for field work).
NB	Suitable; conditional independence assumption may be unsuitable and other algorithms might achieve better accuracy.
Optimization, Robotics and Controls: The data collected for these applications varies depending on the task (i.e., exploratory, vision, learning-based controls, etc.). Large data sets, noisy, incomplete and highly uncertain data can be found in this area. Synthetic data-based problems are presented which can remove some data related issues. Combinations of algorithms are also common (e.g., neuro-evolution).	
DT	Unsuitable; missing information, data variation affects the performance.
ANNs	Suitable for most applications, especially for reinforcement learning (controls).
NN	Not suitable for large, uncertain, and noisy datasets.
SVM	Suitable; however, keep in mind scalability and hyperparameter tuning.
NB	Likely unsuitable due to conditional independence assumption; more general Bayesian networks might be more suitable.

computing[2], which allow for users with limited resources to access services at lower costs, such as intensive multi-physics simulations Wu et al., 2013.

5. Conclusion

This study presents a review of various applications of machine learning to the field of nuclear science and associated engineering. It is the authors' intent that this review helps provide researchers with a background and guidance to understand the benefits of new technologies as applied to the nuclear science domain to enable and accelerate the scientific and technological outcomes of learning-based approaches. Furthermore, it is crucial that the primary goal for the development and implementation of machine learning algorithms is to provide fast estimation for better informed decisions for the users (human in the loop), as well as assuring interpretability and reproducibility of the models. Lastly, to accelerate innovation the use modern research accelerators that allow for active (virtual) discussion and collaborations is encouraged. Ultimately, the goal is a safe and effective application of learning-based method in nuclear science.

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[2] Morrisett et al. (2019), Fernandez Molanes et al. (2018) and Freedman (2017) note some of the current trends and challenges and opportunities regarding to cloud-based computing and IoT as related industry and research applications.

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