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Review

Artificial intelligence in nuclear industry: Chimera or solution?

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A B S T R A C T

Nuclear industry is in crisis and innovation is the central theme of its survival in future. Artificial intelligence has made a quantum leap in last few years. This paper comprehensively analyses recent advancement in artificial intelligence for its applications in nuclear power industry. A brief background of machine learning techniques researched and proposed in this domain is outlined. A critical assessment of various nuances of artificial intelligence for nuclear industry is provided. Lack of operational data from real power plant especially for transients and accident scenario is a major concern regarding the accuracy of intelligent systems. There is no universally agreed opinion among researchers for selecting the best artificial intelligence techniques for a specific purpose as intelligent systems developed by various researchers are based on different data set. Interlaboratory work frame or round-robin programme to develop the artificial intelligent tool for any specific purpose, based on the same data base, can be crucial in claiming the accuracy and thus the best technique. The black box nature of artificial techniques also poses a serious challenge for its implementation in nuclear industry, as it makes them prone to fooling.

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1. Introduction

Artificial intelligence—the mimicking of human cognition by computers—has come a long way since being an imagination in science fiction to becoming a reality in ubiquitous sense of modern technology. The presentiment for artificial intelligence has also transcended from fear to artificial consciousness (Reggia, 2013). Perhaps, the combination of big data and artificial intelligence is being seen as both ‘fourth industrial revolution’ or ‘fourth paradigm of science’ (Jha and Topol, 2016; Agrawal and Choudhary, 2016; Butler et al., 2018). Global energy consumption is projected to increase by 35 percent until 2035 and at present the scientific community is at a fuzzy crossroad about the future energy policies. Few argues that rapid development of nuclear technology is the key to reduce carbon emissions quickly enough to avoid a climate catastrophe (Kharecha and Hansen, 2013; Augutis et al., 2015; Heard et al., 2017) while others assiduously point to feasibility of energy systems only based on renewables (Becker et al., 2014; Brown et al., 2018; García-Olivares et al., 2018). In recent times, a new alternative as hybrid nuclear-renewable energy system is also being proposed (Forsberg, 2013; Ruth et al., 2014; Suman, 2018). Irrespective of what future policy holds for quenching global energy thirst, use of artificial intelligence can be instrumental in ushering innovation for nuclear energy (Adamantiades and Kessides, 2009; Cortés-Borda et al., 2015; Vujić et al., 2012; Yu et al., 2019) either in its independent operation or in cogeneration with renewables.

Idea of applying computational intelligence in nuclear industry for different applications is not recent. Research works (Bernard, 1989; Uhrig, 1991; Reifman, 1997; Uhrig and Tsoukalas, 1999; Hines et al., 2005; Hines and Uhrig, 2005; Moshkbar-Bakhshayesh and Ghofrani, 2013) surveying application of machine learning to nuclear power plants are provided in Table 1.

Bernard (1989) discussed the appropriateness and applications of artificial intelligence to nuclear power plant and control of its process. Unresolved issues in the adoption of artificial techniques to process control is briefly highlighted. It is mentioned in this survey work that there will be much improvement in automated control system if qualitative and quantitative reasoning are combined. Thus, artificial techniques and analytical techniques should not be viewed as competing technologies. Uhrig (1991) succinctly summarised the potential application of neural networks in monitoring of nuclear reactors. Sensor validation, monitoring of thermodynamic performance of plant, vibrations analysis, check valve failure diagnostic, design of fuel cycle reload are few applications explained in this report. Reifman (1997) surveyed artificial intelligence technique used for detecting and identifying faults of a component in nuclear reactors. Artificial intelligence (AI) systems proffered for detection and identification of component faults in nuclear plants are classified on the basis of a) *type of computing approach* b) *type of methodology* and c) *scope of diagnostic system* in this work. Uhrig and Tsoukalas (1999) comprehensively reviewed the application of soft computing methodologies—especially fuzzy logic, neural networks, and genetic algorithms—for the operation, surveillance, and diagnostics of reactor. It was concluded in this review that use of artificial technique, either individually or in combination, has been successfully demonstrated in plethora of investigations conducted using real power plant data at laboratory scale. However, given the concerns about regulatory issues, these technologies are not being readily implemented in nuclear industry. Later Uhrig and Wines (Hines et al., 2005; Hines and Uhrig, 2005) in the two reviews articles pointed that recent activities are gradually shifting focus on implementation of computational intelligence in operational power plants, and also designing of artificial intelligence technique for next generation reactors as well as space reactors is being initiated. It was emphasized that research and execution of such techniques are crucial for safe, efficient, and consistent operation of future reactors, especially those generation IV nuclear power plants that are projected to run semi-autonomously for longer period. Different types of advanced data-driven artificial intelligence techniques for transient identification in reactors were surveyed, evaluated, and compared by Moshkbar-Bakhshayesh and Ghofrani (2013). Even though it was perceived that such transient identifiers would become more efficient and reliable with the progress in model-free methods, a need of further research in this domain was stressed before AI based systems may be fully implemented.

With quantum leap in computational power as well as electronics being getting cheaper, artificial intelligence has made incredible progress in recent times. Nuclear reactors generate around 10% of the global electricity currently and worldwide more than 55 nuclear plants are being constructed at present (Suman, 2018). However, nuclear industry in the aftermath of Fukushima feeling a great stress to innovate especially in developed countries. This paper delineates recent advancement in machine learning for the nuclear power generation after providing a brief background of machine learning techniques researched and proposed in this

Table 1
Summary of reviews on application of artificial intelligence in nuclear reactor.

Author(s)	Focus	Highlights of the review
Bernard (1989)	Reactor and plant control	- Suitability of AI methodologies for process control is justified - Applications of AI in planning, prediction, and assessment of process control is discussed
Uhrig (1991)	Diagnostic and Monitoring of power plants	- Applications of neural networks in diagnostic and monitoring of nuclear power plants is deliberated - Potential of neural network techniques to enhance performance and safety of nuclear reactor is projected
Reifman (1997)	Detecting and identifying faulty component	- A comprehensive classification of AI methods proposed for detection and identification of component faults in reactor is provided - Approaches, scope, and issues of diagnostic system is presented
Uhrig and Tsoukalas (1999)	Operation, surveillance, and diagnostics of reactors	- Application of fuzzy systems, neural networks, and genetic algorithms is shown in context of various specific applications - Use of synergistic relationship between AI technologies is proposed
(Hines et al., 2005)	Autonomous anticipatory control	- Different issues in the operation of nuclear plant where AI can be useful is elaborated - Use of AI in making the operations of Generation IV reactors semi-autonomous is emphasized
Hines and Uhrig (2005)	Reactor noise analysis and plant efficiency improvements	- Role of multi-intelligent systems is argued for safety of nuclear plants
Moshkbar-Bakhshayesh and Ghofrani (2013)	Transient identification in power plants	- Classification and comparison of different transient identification approaches based on AI technologies are surveyed

domain. A critical assessment of various nuances of artificial intelligence for nuclear energy is presented in the form of discussion before arriving at the conclusion.

2. Artificial intelligence methods in nuclear energy

Artificial intelligence is to develop intelligent machines or programs to achieve any desired goal. The notion of intelligence refers to make certain kind of self-decision based on perception of knowledge developed by reasoning and learning. Machine learning, which is a form of artificial intelligence and may be defined as a technique of parsing data, learn from that data and then apply the learning to make an informed decision, finds numerous application in nuclear power reactor—smooth operation of nuclear power plant requires continuous monitoring of numerous parameters which generates huge amount of data or signal. Data based artificial intelligence or machine learning conceptually based on training the machine using data and evaluating its response to get desired results, as shown in Fig. 1.

Machine learning may be broadly classified into three main categories, as presented in Fig. 2, on the basis of methodology used for training the algorithm—supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is that type of machine learning in which output value is explicitly used to train the algorithm. In other words, the algorithm is guided under the supervision of target or output. Usually supervised learning is used for classification or regression of data. Support vector machine, neural network, naïve Bayes are few popular examples of supervised learning. When an algorithm is used to form interpretations using database that consists of only input data, it falls under unsupervised learning. Clustering is the most common application of unsupervised learning method in which algorithm is used to find certain patterns or group in dataset. Reinforcement learning is a type of machine learning where the algorithm responds to maximise the output within constrains of given scenario. The dissimilarity between reinforcement and supervised learning is the output signal that decides whether the step reserved by the algorithm is good or bad (Kaelbling et al., 1996).This section gives a brief overview about few popular machine learning techniques applied in nuclear energy sector.

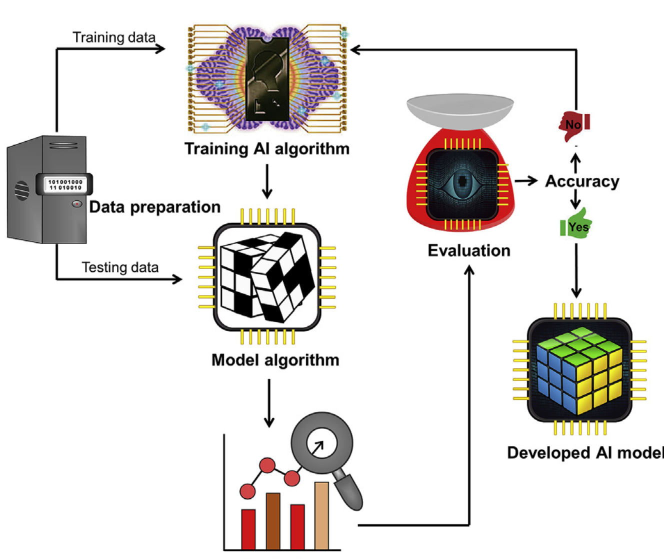

Fig. 1. Typical stages of machine learning.

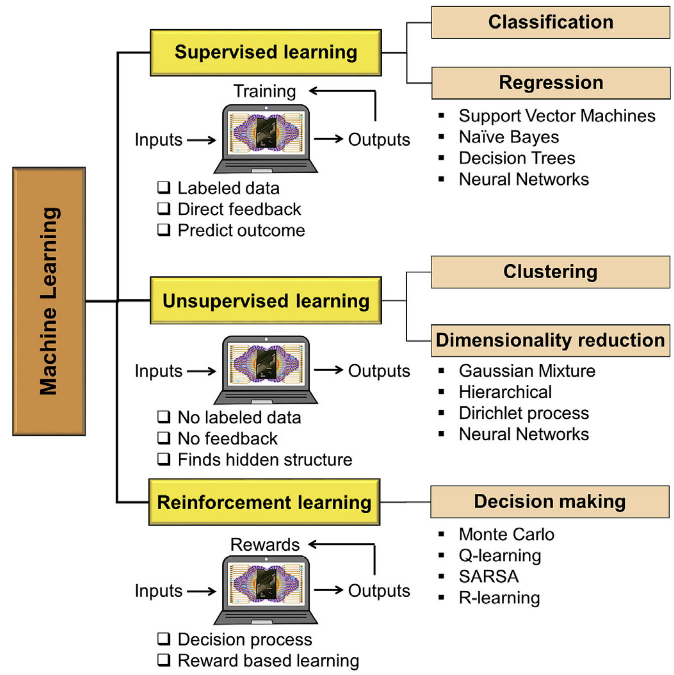

Fig. 2. Classification of machine learning.

2.1. Neural network

Neural Network or Artificial Neural Network (ANN) is the computational model inspired by the animal brain (Mellit et al., 2009). The term 'Neural' is derived from basic functional unit of nervous system of an organism called 'neuron'. The neural network model consists of layers, namely input layer, hidden layer, and output layer, and each layer is made up of neurons. Neuron is also refereed as node. There are different types of neural network based on learning algorithm applied during the training of network such as backpropagation neural network, feedforward neural network, convolutional neural network, radial basis neural network, recurrent neural network etc. The most widely used learning algorithm for neural network is backpropagation (Youssef et al., 2017). Neural networks find numerous applications in forecasting, control, modelling, pattern recognition etc.

2.2. Genetic algorithm

A genetic algorithm is a heuristic technique that is inspired from phenomenon of natural evolution. In other words, genetic algorithm imitates the process of natural selection wherein next descendants are reproduced by fittest individuals at the present generation. In this method, there is an initial population of genes. The best genes in the population is determined using a fitness function. Based on functions defined for mutation and crossover, the genes producing the best output for fitness function are chosen to produce the next cycle of genes. The process of changing some genes in the sequence is called mutation and it is essential to sustain diversity within the population and constrain non-optimised convergence. Crossover is another important phase in a genetic algorithm where two chromosomes pair up and exchange segment of their genetic characteristics. Crossover point are selected randomly among genes for each pair of population to be copulated. Genetic algorithm has been used in efficiency optimisation of energy system, traffic signal coordination, timetable scheduling etc.

2.3. Particle swarm optimisation

Particle swarm is a stochastic optimisation technique which is established drawing inspiration from shared behaviour of fish schooling or bird flocking. This technique has many characteristics similar to other evolutionary techniques like genetic algorithms. Initialisation of a problem is done with a population of random solutions and optima is searched by replacing with better fitness value each time in an iterative way. However, unlike genetic algorithm, this technique has no evolution functions such as mutation or crossover. The possible solutions, which are termed particles, traces the space of given problem based on optimum value path of current generation particles (Jain et al., 2018). Few applications of particle swarm optimisation are finding maximum efficiency of solar collectors, management of ground water resources, vehicle routing etc.

2.4. Ant colony

The ant colony optimisation is based on behaviour of ant looking for a path between their location and a source of food. When searching for food, ants make a trace of chemical pheromone on the travelled path. Once any ant locates a source of food, it carries a portion of food back to nest. While making this journey from food source to nest, the quantity of chemical pheromone left by ant on the path depends on the quality and quantity of the food at source. Path that has stronger concentrations of pheromone is most probable to be chosen by following ants during search of food (Blum, 2005). Usually, ant colony optimisation is most suited for problems which are very dynamic in behaviour. The central characteristics of this technique is the ability to run any calculation steadily while adapting to changes progressively.

2.5. Artificial bee colony

Artificial bee colony method is motivated by intelligent behaviour of bees. The aim of bees is to find new sources of food and in this search technique it can be thought like search space. The source of food for bee should be with high amount of nectar which can be thought like good fitness value for the search function. As in nature, three different types of bees are employed in this method: (a) bees flying randomly without any guidance within the search domain are called scout bees (b) bees using neighbourhood space to select a random solution in order to perturb are called employed bees (c) and the bees who utilises fitness function to select the probabilistic solution exploiting neighbourhood space are called onlooker bees. These bees work on concept of greedy selection meaning if the amount of nectar at a new location is higher than previous one in their memory, they update the memory with recent location and forget the old one. If a predetermined number of trials does not improve the solution, then employed bee abandons the corresponding food source and it becomes a scout bee (Karaboga and Basturk, 2007).

2.6. Simulated annealing

The simulated annealing algorithm is established drawing motivation from the way metals cool from any high temperature. The cooling makes metal to achieve state of lowest-energy and it happens in a progressive way that is characterised by decrease in atomic movements (Kirkpatrick et al., 1983). Likewise, this algorithm produces a new possible solution by altering the existing state of the considered problem according to a predefined criterion. This algorithm is suitable for finding global optima as it is not saturated at any local optima present in search space.

2.7. Support vector machine

Support vector machine (SVM) is a supervised machine learning technique capable of decrypting elusive features in cluttered and noisy datasets and it is employed for linear as well as non-linear classification (Andrew, 2001). The training programs for this algorithm is based on concept of functional margin which develops a deterministic binary linear classifier. Based on the number of classes employed for training the algorithm of a particular class, this method can be broadly classified as: (a) Multiclass SVM: the tags are taken from a finite set of several features (b) Transductive SVM: based on partially tagged elements in semi-supervised learning based on transduction (c) Structured SVM: the search space is structured and usually of infinite size (Andrew, 2001). Usually support vector machines outperforms neural network and decision tree techniques in the absence of a large training data set and has been very widely used across all disciplines (Tong et al., 2013).

3. Applications of artificial intelligence in nuclear industry

Nuclear industry is striving to innovate and firms around the world are developing new nuclear reactor technologies marketed as inherently safe, clean, affordable, flexible, and reliable. Existing nuclear power plants are committed to improve safety, maintain availability, and reduce operation and maintenance cost. Research focused on fusing the capabilities of artificial intelligence in nuclear industry has come a long way and time may have come to inculcate this in future nuclear power plants. Following are the major applications of artificial intelligence techniques in nuclear industry:

3.1. Operation of nuclear power plant

To support the operators of a nuclear reactor in their knowledge-based actions and to allow them to make a quick decision during abnormal events, Takizawa et al. (1994) developed and patented (Method and apparatus for, 1997) an intelligent man-machine system. It assisted the operator in three ways, namely by enhancing cognitive resource, reducing workload using robust automatic controller, and assisting with analytical reasoning during abnormal events. The validations tests were executed with experienced operators and the results confirmed that the developed intelligent man-machine system was extremely helpful in coping with complex plant situations. Guo and Uhrig (1992) developed artificial neural network to predict the efficiency or thermal performance of a nuclear reactor using the heat rate measurements data acquired for a period of one year. It was concluded that application of such neural network model may provide useful information regarding the cause of deviation in heat rate and thermal performance, and will help in running the reactor more efficiently. Nabeshima et al. (NABESHIMA et al., 1998) utilized artificial neural network for developing a real time monitoring system for a nuclear power plant. They tested this system for both of-line and on-line case of the reactor, and it was observed that monitoring system worked satisfactorily and capable of real time monitoring of the power plants. This monitoring system detects abnormal signals in a very quick way and provides personnel enough time to manage with this in order to avoid shutdown of plant that can cause huge loss. Few researchers like Abbott et al. (1983), Fernandez et al. (Gomez Fernandez et al., 2017), Zeng et al. (2018) also successfully illustrated the use of artificial intelligence techniques for the automation of control and safety systems in nuclear reactors. Zio et al. (Zio et al., 2010; Zio and Di Maio, 2010) used fuzzy approach to identify the failure scenario in a nuclear power plant systems and predicting its remaining useful life. This tool is found to be extremely helpful in planning for proactive maintenance as well as devising safety procedures.

3.2. Fuel management

Uranium undergoes controlled fission to produce heat energy in nuclear power plant. Uranium is kept in form of a pellet inside a tube called cladding tube that acts as heat transfer interface. These tubes are bundles together in different sizes depending upon the power generation capacity of the plant and it is called fuel bundle. Fuels and the additional components of a power plant change during irradiation and therefore design of core of reactor must consider changes in thermal, mechanical, neutronic, and chemical properties, keeping in mind that a change in one property might affect another property. Nuclear fuel management entails decision making about the quantity and the features of the new fuel assemblies, the partly burnt fuel assemblies that will be re-loaded, the core-loading pattern and even the planning for control rod insertion for each reload cycle. Fuel design is in a continuous process of improvement for the constant effort of better fuel utilisation, enhanced heat removal, safer and more economical construction and increased operational efficiency. In other words, the primary objectives of nuclear fuel management are to minimise cost while optimising energy requirement and keeping safety as the prime determinant. Table 2 summarises research focused on use of artificial intelligence in nuclear fuel management.

Hedayat et al. (2009) optimised the research reactor core pattern using cascade feed forward ANN. They observed that selection of the type and architecture of neural network, activation and learning functions have significant effects on the performance of the neural network model. It was concluded that developed neural network estimates the core parameters very quickly and improves optimisation process of the pattern of the core reload program effectively. Pazirandeh and Tayefi (2012) also applied another type of neural network, namely Hopfield neural network to optimise fuel management in a water-cooled, water moderated energy reactor or VVER. Their research found that the use of neural network technique improves the radial, axial, and total power peaking factor. Erdoğan and Geçkinli (Erdoan and Geçkinli, 2003) developed a computer package named XCore based on genetic algorithm and artificial neural network to assist in-core fuel management for a pressurised water reactor. The software package combines the stochastic optimisation capability of genetic algorithm with the powerful learning from data ability of deep neural networks. They mentioned that XCore makes the process extremely faster and a large number of loading patterns can be evaluated, thus increasing the probability of finding a desired optimum. Norouzi et al. (2013) used genetic algorithm coded with parallel integer to achieve the best arrangement of fuel assembly considering maximum multiplication factor. On evaluation of this algorithm, they found that the convergence rate, results, and reliability of the model are reasonably favorable and it offers significant gains in

Table 2
Summary of research on application of artificial intelligence in fuel management.

Ref.	Technique	Application	Findings
Erdoan and Geçkinli (2003)	Artificial neural network and GA	In-Core fuel management	- A program based on combination of genetic algorithm and neural network is developed
Ziver et al. (2004)	Artificial neural network and GA	Fuel loading pattern	- ANNs may be included to fasten the optimisation process, but it is computationally expensive to get good accuracy
de Lima et al. (2008)	Ant colony system	Fuel reload pattern	- Artificial ant colony network provides results superior to genetic algorithm
Hedayat et al. (2009)	Artificial neural network	Reactor core parameters	- core parameters are estimated faster and fuel reload pattern improves effectively
Martín-del-Campo et al. (2009)	Flexible GA	Fuel loading pattern	- A binary representation of the solution was applied to provide a flexible treatment in algorithm
Babazadeh et al. (2009)	Particle swarm optimisation	Fuel loading pattern	- Procedure can aid in achievement of a new pattern without violation of constrictions
Khoshahval et al. (2010)	particle swarm intelligence	Fuel reload pattern	- constricted factor approach PSO outperformed the established GA and Hopfield methods
Khoshahval et al. (2011)	Particle swarm optimisation and GA	Fuel loading pattern	- GA is computationally costly than that of PSO - performance of both GA and PSO is quite satisfactory
Safarzadeh et al. (2011)	Artificial bee colony	Fuel loading pattern	- Performance is adequate and comparable to GA and PSO
De Oliveira and Schirru (2011)	Artificial Bee Colony	In-Core fuel management	- Artificial bee colony with random keys is superior to genetic algorithm and particle swarm optimisation
Montes et al. (2011)	Ant colony system	Fuel lattice design	- Ant colony technique is a potent algorithm to find for the best fuel arrangement pattern
Lin and Lin (2012)	Particle swarm optimisation	Fuel lattice design	- Fuel lattice composition is designed automatically
Pazirandeh and Tayefi (2012)	Artificial neural network	Fuel management	- Radial, axial, and total power peaking factor are improved
Liu and Cai (2012)	Pivot particle swarm	Fuel loading pattern	- Optimised arrangement proved to have advantage in economic efficiency and safety
Lin and Hung (2013)	Particle swarm optimisation	Multi-cycle fuel reload	- Multi-cycle fuel loading patterns is designed automatically
Norouzi et al. (2013)	Genetic Algorithm	Reactor core optimisation	- Satisfactory performance with significant reduction in computational cost
Safarzadeh et al. (2014)	Hybrid artificial bee colony	Fuel reload pattern	- Merits of artificial bee colony and particle swarm intelligence are combined
Poursalehi et al. (2015)	Effective Discrete Firefly	Fuel reload pattern	- Effective discrete firefly is superior to continuous firefly, and discrete firefly algorithm
Kumar and Tsvetkov (2015)	Genetic algorithm	Reactor core design	- A set of parameters for design of the reactor is optimised using genetic algorithms, and multivariate regression analysis
Jayalal et al. (2015)	Genetic algorithm	Fuel bundle burnup	- Multi Objective GA is superior to Penalty Functions based GA in performance, however, latter is less computationally expensive
Ortiz-Servin et al. (2018)	Population-based metaheuristics	Fuel lattice design	- Computationally less expensive solutions are obtained fulfilling energy requirements and ensuring core safety
Akbari et al. (2018)	Imperialist Competitive Algorithm	Fuel loading structure	- Algorithm showed a high potential on comparing its optimised results with results developed by reactor engineer

computational cost. Kumar and Tsvetkov (2015) coupled the genetic algorithm and multivariate regression analysis to optimise a set of parameters in the fuel design of a nuclear reactor. They optimised a number of design parameters like radius of a fuel pin cell, neutron multiplication factors, fuel burn-up etc. by making separate module for each parameters, and then merging them at last to have the best performing parameters for the reactor. It was cautioned that during meeting the specific optimisation objective, use of genetic algorithm could lead to a local minimum or a non-unique set of parameters. Jayalal et al. (2015) also applied two different methodologies of genetic algorithm, namely penalty functions based genetic algorithm and multi-objective genetic algorithm exclusively for fuel bundle burnup optimisation of pressurised heavy water reactor. They found that multi-objective genetic algorithm is better in convergence speed and yields more non-unique set of solutions. The ability of multi-objective genetic algorithm in generating larger set of non-unique solutions is a desired feature of the fuel bundle burnup optimisation problem as it helps power plant operator in having more options when deciding the appropriate discharge burnups of the core zones. Lin and Lin (2012) developed an automatic algorithm based on a particle swarm optimisation to design the fuel lattice of a boiling water reactor. Their results obtained using this automatic procedure demonstrated that the fuel lattice design parameters are comparable with those of the reference fuel assembly. The advantage of automatic algorithm was that this can easily generate and test several lattice designs, and the best fuel zones can be assembled in accordance with the core simulation results. For fuel lattice design optimisation of a boiling water reactor, Montes JL et al. (Montes et al., 2011) used ant-colony model. It was concluded that this approach makes it possible to have more than one suitable solution, all of them being very close to lattice parameters of reference fuel assembly and thus this approach represents a powerful tool to tackle this step of the fuel design that may be accomplished within hours. Oliveira and Schirru (De Oliveira and Schirru, 2011) attempted to find the best fuel lattice design of a pressurised water nuclear reactor to maximise the operating time using artificial bee colony technique. They also applied genetic algorithm and particle swarm optimisation techniques for the same and the outputs verified that the artificial bee colony is superior to genetic algorithm and a little better than particle swarm optimisation. Moreover, artificial bee colony offers flexibility of using lesser number of parameters for controls.

The prime challenge in determination of fuel assembly pattern is possibility of a large number pattern combinations within the reactor core. Moreover, given this is a discrete and nonlinear problem, it poses difficulties in the use of conventional optimisation techniques. Ziver AK et al. (Ziver et al., 2004) adopted a non-generational genetic algorithm to optimise the fuel pattern of generation IV gas-cooled nuclear plant. Artificial neural networks were used to propel the genetic algorithm-based pursuit during finding the best value. The results proved that this approach could aid the personnel to optimise loading patterns in a proficient and more economic way compared to conventional way for multi-cycle refueling of advanced gas-cooled reactors. They also mentioned that even though artificial neural network may be used to fasten the optimisation model, but higher computational cost is needed to achieve high accuracy. Martín-del-Campo (Martín-del-Campo et al., 2009) used flexible genetic algorithm for fuel loading pattern optimisation for boiling water reactors and compared their results with experimental results. The developed optimisation algorithm illustrated better effectiveness and flexibility. Babazadeh D et al. (Babazadeh et al., 2009) developed a particle swarm optimisation algorithm to decide best pattern of fuel core in a VVER plant and mentioned that highly precise results can be obtained by including more input parameters. Liu and Cai (2012) used pivot particle swarm method and Safarzadeh et al. (2011) applied artificial bee colony algorithm to optimise fuel loading pattern for a pressurised water reactor. The results of both studies demonstrated the potential of such artificial intelligence techniques for optimisation of fuel loading patterns in nuclear power plant. Khoshahval et al. (2011) evaluated the performance of both particle swarm optimisation and genetic algorithm for fuel loading pattern optimisation of a pressurised water reactor. They observed that even though performance of both particle swarm optimisation and genetic algorithm is satisfactory, the computation time for genetic algorithm is too high in comparison to particle swarm optimisation.

In nuclear power plant, decayed fuel bundles are ejected and refilled with fresh fuel bundles periodically. To maximise the use of fissile fuel, and optimum reload designed has to be developed. Optimal fueling design refers to an arrangement which gives maximum fuel cycle time or uses minimal quantity of fuel in a given period while adhering to regulating constrains like power peaking factor. Khoshahval et al. (2010) designed a core reload optimisation package using particle swarm optimisation technique for a pressurised water reactor. Lima et al. (de Lima et al., 2008) developed artificial ant colony based procedure to answer the fuel reload optimisation problem of a pressurised water reactor. Both of these studies (de Lima et al., 2008; Khoshahval et al., 2010) mentioned that for all the investigated cases, their technique yielded results far superior to results of genetic algorithms. Safarzadeh et al. (2014) used the particle swarm optimisation and hybrid of artificial bee colony algorithms— integrating the merits of both—to maximise the fuel cycle length of a VVER. It is observed that combined approach produces faster and reasonably accurate solutions. Lin and Hung (2013) developed an automatic multi-cycle fuel reload pattern package for a pressurised water reactor based on particle swarm optimisation algorithm. The results proved that this tool could realize the desired task and it is highly useful for fuel loading designer.

3.3. Fault diagnosis in nuclear power plant

Fault diagnosis refers to is the practice of locating any abnormal behaviour of a component based on certain indicators. Precise identification of faults in multifaceted systems like nuclear power plant needs getting the data through sensors, treating the data using algorithms, and mining required pattern for useful identification or classification of faults (Galar et al., 2017). With rapid progress in artificial intelligence, researchers have proposed various new approaches for fault diagnosis in nuclear power plants. Table 3 provides a summary of research focused on use of artificial intelligence for fault diagnosis in reactor.

Bartlett and Uhrig (1992) developed a diagnostic system based on artificial neural network to predict the operating status of nuclear power plant. The developed neural network is trained using data from both normal operating conditions as well as potentially unsafe conditions like loss of coolant accidents, loss of off-site power, steam generator tube leak etc. The feasibility of this diagnostic tool on the basis of ANN was demonstrated and it was emphasized that use of more variables and training of model with many more accident conditions would make it more applicable for real power plant monitoring. Şeker et al. (2003) used recurrent neural network—network in which outputs of few neurons are served back to same neurons or to previous layer neurons—for conditions monitoring and fault diagnosis in nuclear power plant. It was observed that the recurrent neural network is very sensitive to even a small perturbation induced in the signals and thus adequately they can be used for monitoring of nuclear power plant. Liu et al. (2014) used hybrid intelligence approach fuzzy neural network for fault diagnosis in nuclear power plants. They mentioned that since nuclear

Table 3
Summary of research on application of artificial intelligence for fault diagnosis.

Ref.	Technique	Application	Findings
Bartlett and Uhrig (1992)	Artificial Neural Network	Operating status of power plant	- Feasibility of using neural network technology as a diagnostic tool at reactor is demonstrated
Fantoni and Mazzola (1996)	Artificial Neural Network	Identification of sensor failures	- Promptly detected the failed sensors with maximum uncertainty of 5%
Şeker et al. (2003)	Artificial Neural Network	Plant condition monitoring	- Highly capable of detecting dynamical changes in signals
Liu et al. (2014)	Fuzzy Neural Network	Fault diagnosis	- Use of hybrid intelligence approach is emphasized
Hatami et al. (2014)	Neuro-fuzzy	Power control of reactor	- Fault tolerant control system is designed for power changes operation in reactor
Hatami et al. (2016)	Neuro-fuzzy	Identification of operational parameters	- Coolant reactivity coefficient and fuel reactivity coefficient for failure scenario is identified
Ghazali and Ibrahim (2016)	Neuro-fuzzy	Transducer and actuator condition	- Developed model may be used for online fault detection and analysis
Peng et al. (2018)	Deep Neural Network	Fault diagnosis	- Developed model outperformed the models based on conventional back propagation neural network and support vector machines

power plants are extremely complex system with possibility of different types of faults, a hybrid approach is better for correlating between a specific fault and its symptoms. On testing their fuzzy neural network model through simulation of different accident scenarios, improvement in fault diagnosis efficiency was verified. However, it was mentioned that it should be ultimately tested under actual operating conditions in nuclear power plants. Peng et al. (2018) applied a class of deep neural network to develop a fault diagnosis model for nuclear power plant. They trained the model using data obtained for seven different operating statuses of power plant—six different faulty conditions and the normal steady state. The developed deep neural network shown remarkable accuracy of above 99%, and it was found to be far superior than the performance of models developed using back propagation neural network and support vector machines in their study which have accuracy about 95% and 93%, respectively. Hatami et al., 2014, 2016 applied adaptive neuro-fuzzy technique to design a fault tolerant intelligent control system for the power plant during operational power change. They tested this fault tolerant control system under various failure scenario like loss of coolant accident, ejection of control rod etc. and found that it has satisfactory parameters tracking performance and robust stability against failures. Fantoni and Mazzola (1996) used artificial neural networks for identification of sensor failures in boiling water reactor while Ghazali and Ibrahim (2016) used neuro-fuzzy inference algorithm for online detection of sensor conditions, and the model showed good performances by promptly detecting the failing sensors.

3.4. Identification of nuclear power plant transients

A transient may be defined as an undesirable progression where any components transmutes into an unusual state from a normal state (Zhou et al., 2017). For nuclear power plant, transients are probable events which is anticipated to occur at least once during its lifetime operation— also termed as anticipated operational occurrences. Transient in nuclear power plants is caused by failures and faults that are related to components inability in executing its chosen function and components nonconformity from the expected condition, respectively (Moshkbar-Bakhshayesh and Ghofrani, 2013), few examples of transients are steam generator tube ruptures, not maintaining the desired flow of coolant to the reactor vessel, malfunction of a control system etc. In order to prevent escalation of transients to accidents and achieve greater safety as well as economic benefits, it is very crucial detecting and identifying transients within quickest time during the operation of reactors. Table 4 lists research focused on use of artificial intelligence related to nuclear power plant transients.

Embrechts (Embrechts and Benedek, 2002) purposefully generated seventeen different types of transients at Hungarian full-scale training simulator of the Paks nuclear power plant. Using the generated data, various ANN based models were developed to recognize the transients. It was found that feedforward neural networks trained with the backpropagation gives the best result. He also concluded that more deviations primarily took place in the identification of transients that were unlabeled. Santosh et al. (2007) also did extensive work on different training algorithms of ANN to recognize the transients of a typical reactor and found that resilient-back propagation algorithm is the best choice for this purpose. Mo et al. (2007) proposed a dynamic neural network aggregation model—uses a two level classifier architecture, unlike conventional neural network which has single level classifier— for transient identification and classification in nuclear power plants. Separate artificial neural network model was assigned for each determining transients' type, severity, and location. On testing with simulated transients' data, it was observed that dynamic neural network aggregation model had a satisfactory performance; however, it yielded a better performance compared to conventional artificial neural network. Zio and Baraldi (2005) also attempted to identify the type of nuclear transients using fuzzy clustering approach. A set of 2800 patterns has been used to train the classifier and its performance was tested with other 700 patterns. Even though a good enhancement in accuracy was achieved, it was still wanting for further improvement. Ayo-Imoru and Cilliers (2018) developed artificial neural network to identify transients and detect fault in a running nuclear power plant. They mentioned that it is easier to detect fault in a steady state of power plant compared to plant in operating state. The nuclear power plant simulator was used as dynamic reference for detecting the transients and faults of a power plant in transient. It was observed that for successful implementation of this method, the accuracy of the plant simulator, which acts as dynamic reference, in correctly mimicking the real plant is of paramount importance. Different other techniques like particle swarm optimisation (Carlos Canedo Medeiros and Schirru, 2008), template matching (Lin and Chang, 2011), and multivariate algorithms (Wu et al., 2018) have also been applied for identification of reactor plant transients with reasonable success.

3.5. Identification of accident scenario

Unlike transients, the accidents are events hypothesised but not likely to occur during the lifetime of plant. Burst of coolant pipe connected to reactor vessel, breakdown of the pump pumping coolant to the plant core the reactor core, ejection or drop of a control rod are few examples of accident scenario. The efficient

Table 4
Summary of research on application of artificial intelligence for transient identification.

Ref.	Technique	Application	Findings
Embrechts and Benedek (2002)	Artificial Neural Network	Identification of plant transients	- Back propagation method proved to be the best against the deceptive identification of untagged transients
Zio and Baraldi (2005)	Fuzzy clustering	Classification of transients	- Methodology is applied successfully to the classification of U-tube steam generator
Santosh et al. (2007)	Artificial Neural Network	Plant transients diagnosis	- Resilient-back propagation method converged fastest and delivered the best result
Mo et al. (2007)	Dynamic Neural Network	Transients' type and severity	- Quick detection and more accurate prediction of severity
Carlos Canedo Medeiros and Schirru (2008)	Particle swarm optimisation	Reactor plant transients	- Searching the best set of prototypes for identification of transients is proposed
Lin and Chang (2011)	Template matching	Reactor plant transients	- Transients outside of data set like Three Mile Island accident, and a turbine trip without bypass are detected successfully
Ayo-Imoru and Cilliers (2018)	Artificial Neural Network	Identification of faults in transients	- Using plant simulator as a dynamic reference improves performance
Wu et al. (2018)	Multivariate algorithms	Initiating event detection	- Methodology is evaluated using the data generated by a simulator and results agreed well

management of an accident scenario requires the operator to assess a number of complex signals and take necessary actions in a very short time. One of the main postulated design-based accidents is Loss-of-Coolant Accident (LOCA). LOCAs are postulated accidents that cause a reduction of coolant water at a speed higher than ability of the reactor backup system. If not addressed properly, LOCA could damage the core of reactor and that is why every reactor has emergency core cooling system exclusively to handle such scenario. Table 5 lists research focused on use of artificial intelligence in nuclear reactor during accident scenario.

Gomes and Medeiros (Gomes and Canedo Medeiros, 2015) used neural networks with Gaussian radial basis functions to identify the type of nuclear accidents postulated for a pressurised water reactor. They trained the neural network model with data generated by computer simulation of a nuclear power plant Angra II operating with 100% of rated power for three design-based accidents: loss of coolant accident, loss of external electric power, and steam generator tube rupture. It was found that the model is capable to classify all three types of nuclear accidents correctly even when the signals were adulterated with noise level up to 10%. Pinheiro and Schirru (2019) used genetic programming technique to also identify and classify the same three types of accidents. They proved that genetic programming is capable of correctly identify the nature of accidents in very reasonable time as well as this technique requires a very little priori knowledge of the data. Santosh et al. (2009) used thermal-hydraulic code to generate time-dependent transient data for a nuclear plant operation with an assumption of core being in equilibrium and based on this data an operator support system called symptom-based diagnostic system was made. This diagnostic package was developed using artificial neural network and this system was tested for the large break LOCA as a pilot study. It successfully detected the transient change in parameters' value for the process

Table 5
Summary of research on application of artificial intelligence for identification of accident scenarios.

Ref.	Technique	Application	Findings
Na et al. (2004)	Fuzzy Neural Network	Break location and size in loss of coolant accident	- Developed model identifies break locations as well as estimate the break size accurately
Cadini et al. (2008)	Artificial Neural Network	Maximum cladding temperature	- Predicts the maximum fuel cladding temperature well and importantly also give associated uncertainty
Bae et al. (2009)	Support Vector Machines	Power peaking factor	- Model found to be accurate enough for use in core protection and monitoring based on power peaking factor
Santosh et al. (2009)	Artificial Neural Network	Loss of coolant accident	- Demonstrated its role as an efficient operator support system for accident management
Gomes and Canedo Medeiros (2015)	Artificial Neural Network	Identification of nuclear accidents	- Even with a noise level up to 10%, the model identify the nature of accidents accurately
Kim et al. (2015)	Fuzzy Neural Network	Prediction of hydrogen concentration	- Able to predict the hydrogen concentration in containment at a specific time
Choi et al. (2016)	Fuzzy Neural Network	Prediction of hydrogen concentration	- Root mean square error of the model is less than 5%
Kim et al. (2016)	Fuzzy Neural Network	Pressure vessel water level estimation	- Capable of accurately estimating the nuclear reactor vessel water level in severe accident circumstances
Choi et al. (2017)	Fuzzy Neural Network	Break size in loss of coolant accidents	- Accurately predict the break size, root mean square error of the model is less than 0.7%
Yoo et al. (2017)	Support Vector Machines	Identification of loss of coolant accidents and its break location with size	- Model can accurately identify the loss of coolant accidents and their break locations with size
Souza et al. (2017)	Artificial Neural Network	Identification of an accidental drop of a control rod	- Lack of experimental data constrained the efficacy of the proposed model
Tian et al. (2018)	Artificial Neural Network	Break size estimation in loss of coolant accident	- Interpolation pre-processing method to generate more data is found to be effective to enhance performance of model
Koo et al. (2018)	Artificial Neural Network	Pressure vessel water level estimation	- Deep neural network model has better performance than fuzzy neural network model
Saghafi and Ghofrani (2018)	Artificial Neural Network	Break size estimation in loss of coolant accident	- Model was able to directly deal with the time dependent signals for dynamic estimation of break sizes in real time
Pinheiro and Schirru (2019)	Genetic programming	Identification of nuclear accidents	- Model demonstrated high accuracy even with a little priori knowledge of the data.

against the value of same parameters during normal functioning. It was concluded that this artificial neural network based system could be used as a competent personnel aid system during uncharacteristic situations for accident management. Na et al. (2004) used a probabilistic neural network to identify the break locations like hot-leg, cold-leg or steam generator tubes during loss of coolant accidents and coupled this with fuzzy neural network to estimate the size of break. The prosed model was designed and verified by using the data obtained from numerical simulation performed using modular accident analysis program code. The algorithm accurately identified the locations of break as well as estimated the break size with high accuracy. In order to predict break size during loss of coolant accidents, Choi et al. (2017) developed cascaded fuzzy neural network model and applied a hybrid method combined with a genetic algorithm and a least squares method to train this model—using the data obtained from modular accident analysis program code, similar to Na et al. (2004). They concluded that the performance results of the cascaded fuzzy neural network model are better than fuzzy neural network with maximum root mean square error of 0.7%. Tian et al. (2018) also used different architectures of artificial neural network for break size estimation during loss of coolant accident and found that generating more number of data using interpolation during data preparation or data pre-processing is an effective way to improve the robustness of a neural network model to predict break size. Model trained with cubic spline interpolation pre-processing exhibited the best robustness. Saghafi and Ghofrani (2018) also succeeded in developing artificial neural network model capable of directly dealing with the time dependent signals for dynamic estimation of break sizes during loss of coolant accidents in real time and claimed that it can be used to assist operators in planning appropriate accident management countermeasures during loss of coolant accidents. In case of loss of coolant accident, the coolant water would be very rapidly lost coolant from the reactor pressure vessel, which contains the nuclear core. Also, this may increase the temperature of fuel cladding tube—a thin hollow cylindrical tube which encases uranium fuel undergoing fission—and cause the rapid oxidation of cladding tube during which hydrogen is liberated. The hydrogen concentration must be kept below 4% to maintain the integrity of pressure vessel and prevent explosion. Kim et al. (2016) applied a cascaded fuzzy neural network to estimate the reactor vessel water level in the event of a severe accident. The model was developed using the simulated data obtained from modular accident analysis program code and the results showed that the performance of the developed cascaded fuzzy neural network model was satisfactory. Koo et al. (2018) used deep neural network for estimation of water level in reactor pressure vessel during severe accidents using the data obtained from same program as Kim at al. (Kim et al., 2016), and found that deep neural network with maximum error of 0.78% is far better than cascaded fuzzy neural network which had maximum error of 3.24%. This superior results of neural network for pressure vessel water level estimation during severe accidents is in contrast to results of Choi et al. (2017) who found cascaded fuzzy neural network better for prediction of break size during loss of coolant accidents. Choi et al. (2016) also used cascaded fuzzy neural network to predict the hydrogen concentration in nuclear power plant containment under severe accidents, and results were more accurate compared to prediction obtained by using conventional fuzzy neural networks in the study of Kim et al. (2015). Artificial intelligence techniques have also been satisfactorily applied for predicting maximum fuel cladding temperature (Cadini et al., 2008), estimating the burst temperature during loss-of-coolant accidents (Suman, 2020), monitoring of power peaking factor (Bae et al., 2009) or identification of accidental drop of a control rod in the nuclear core (Souza et al., 2017).

3.6. Miscellaneous interesting applications

Operational time of nuclear power plants personnel is constrained by annual radiation dose limit decided by regulatory authority. Enhanced planning of maintenance and operational tasks can decrease radiation dose exposed to worker. Mól et al. (2011) developed a tool to map the radiation dose rate in different area of nuclear power plants using neural network. Use of neural network enabled to predict the radiation dose rate even at various level of power and different locations. They concluded that this neural network based tool might be used for better training or scheduling of worker.

Pressuriser system in nuclear power plant has critical functions of maintaining the coolant level in the core and defined pressure in the primary heat transport system. Oliveira and Almeida (2013) developed a pressuriser model for reactor using ANN. Data from 2785 MWth Westinghouse pressurised water reactor simulator was used to train the neural network model. Artificial neural network was based on feedforward backpropagation learning algorithm and has structure of 19-13-1, which is nineteen input layers, one hidden layers with thirteen nodes, and one output layer. The responses of neural network model matched reasonably well with those of the Westinghouse simulated power plant pressuriser data. A Mamdani-type fuzzy rule based controllers for neural network pressuriser model were also developed and their performance was compared with conventional pressuriser. The pressuriser system developed using neural network and controlled by fuzzy based technique reduced the operational error up to 32 percent as compared to conventional pressuriser system. Brown and Gabbar (Brown and Gabbar (2014) also developed a fuzzy controller to regulate the pressuriser system and compared its performance with the conventional controller used at the Darlington nuclear generating station in Ontario, Canada. It turned out that fuzzy based controller eliminated the problem of overshooting of pressuriser inventory level while also decreased the settling time of the system by seventy-five percent. It was concluded that in spite of nuclear power plant systems being complex and highly transient, the use of artificial intelligent systems could increase system efficiency and decrease risk when a robust controller is designed.

Steam turbines are used for generating electricity in nuclear power plants and in such turbines only a certain fraction of the steam energy is extracted in any stage to keep the turbine blades velocity and centrifugal stress within desired limit. Thus, efficient conversion of steam energy to mechanical energy for electricity generation is achieved in different stages, each with a suitable turbine blade size and range of velocities. Sacco et al. (2002) used genetic algorithm for the evaluation of the optimal fraction of steam energy to be extracted from each stage of the turbines of a pressurised water reactor. This study proved the efficiency and efficacy of the genetic algorithms in finding an optimal combination of stages of turbines to maximise the extraction of steam energy in pressurised water nuclear reactor, and consequently reducing the cost of energy generation.

A number of structural components of nuclear power plant is exposed to radiation field during service. Under these operating conditions, void swelling— increase of volume and decrease of density— occurs with time as radiation induces atomic defects that migrate elsewhere leaving clusters of vacant positions behind in the material. Radiation induced void swelling causes significant mechanical property degradation and dimensional changes which may eventually lead to failure. Jin et al. (2019) used different artificial neural network techniques to predict the onset of void swelling in irradiated materials. Experimental data for material and environmental parameters such as chemical composition, temperature, microstructure, and type of radiation were used as input to predict the onset of void swelling. Their work established the feasibility of artificial intelligence techniques for prediction of macroscale radiation effects or void swelling based on material and environmental parameters, and has practical significance in guiding further material optimisation for nuclear applications. However, it was highlighted that it is critical to enlarge and enrich the input parameter space with more data in future efforts to extract more accurate results.

Residual stress is the internal stress locked into a material, and it exists even in absence of external loading or thermal gradients. Welding is a critical reason that induces residual stress in different components of nuclear power plant and typically generates high tensile stresses. The residual stress developed during welding is severely detrimental to performance and reliability of various components in nuclear reactor like pressure vessel, nozzle etc. (Na et al., 2007). There exist non-destructive techniques like magnetic methods, ultrasonic techniques, diffraction technique etc. to quantify residual stress in a material. However, these techniques are very challenging, expensive, tedious, and always not possible (Rossini et al., 2012). Na et al., 2007, 2008 used fuzzy neural network models and support vector regression while Koo et al. (2017) used cascaded support vector regression technique to estimate the residual stress developed due to welding of dissimilar metals at nuclear power plants. These techniques, namely fuzzy neural network models, support vector regression, and cascaded support vector regression, were developed using same dataset—all these investigations conducted by same research group— and it was found that cascaded support vector regression is the best technique with average root mean square error of 1.51%. Koo et al. (2017) recommended that cascaded support vector regression can be used to assess welded structure integrity in nuclear power plants and it can be very useful in accurate prediction of the residual stress of the reactor pressure vessel and steam generator tube.

Periodic inspection of the components of nuclear power plants is an important preventive step to avoid accidents and ensure safe operation. One of the reasons for accidents is the failure to detect the cracks on components well in advance. A direct inspection inside the core of reactor is not possible, and a typical system deploys a robotic arm equipped with camera to remotely record videos of inside surface. The operator then reviews the videos and identify the cracks. However, this technique is time consuming, tedious and subjective to operator skills. Chen and Jahanshahi (2018) used combined naïve Bayes and neural network based approach to detect crack patches in each frame of the recorded video. The schematic of their developed algorithm is illustrated in Fig. 3. The main advantage of this proposed deep learning-based crack detection is 99.9% true positive rates against 0.1% false positive rates. This artificial intelligent based approach is comparatively very fast and can even detect tiny cracks with low contrast which are hardly recognisable to human eyes, as depicted in Fig. 4.

In case of a severe nuclear power plant accident like Fukushima Daiichi accident in 2011, an evacuation of the area in neighbourhood of the reactor may be ordered to minimise radiation exposure. The dispersion characteristics of radioactive materials, such as direction and range, depends on direction and speed of wind that accompany weather systems. Numerical models to predict the dispersion characteristics of radioactive materials have been developed based on atmospheric parameters of different scale ranging from local wind circulation pattern to monsoons. However, the Japanese government decided not to use model predictions to decide evacuations in future given its limited accuracy (Funabashi and Kitazawa, 2012; Kushida, 2014; Yamada et al., 2017). Yoshikane and Yoshimura (2018) used support vector machine

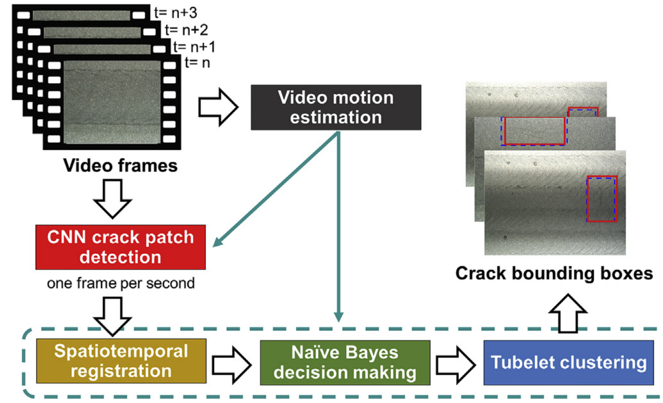

Fig. 3. Concept of the deep learning-based crack detection using naïve Bayes and convolutional neural network.

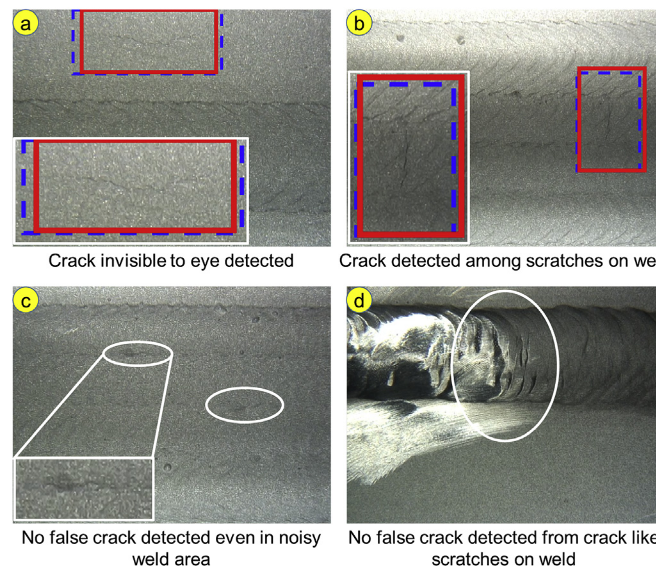

Fig. 4. Sample crack detection results from the developed artificial intelligence framework based on naïve Bayes and convolutional neural network.

algorithm to predict the dispersion characteristics of radioactive materials using near-surface and area average wind data. The flow chart of the developed support vector machine is shown in Fig. 5. Using this machine learning technique, they concluded that directions of dispersion of radioactive materials can be estimated with excellent accuracy up to 33 h in advance based on forecast for winds, as plotted in Fig. 6. Accuracy of more than ninety-five percent is achieved in the month of January and March when local circulation pattern is not that varying.

4. Discussion

Nuclear power reactors are inherently complex and technically challenging engineering system. It has numerous components and interdependent systems that must operate in a precise manner for safe operation and to fulfil all the regulatory guidelines. Moreover, the reactors experience many changes during its service time causing update in monitoring and operational guidelines. The focus of artificial intelligence in the nuclear power sector has been constantly varying because of dynamic nature of nuclear power plant operational objectives, their dynamic needs, and transient

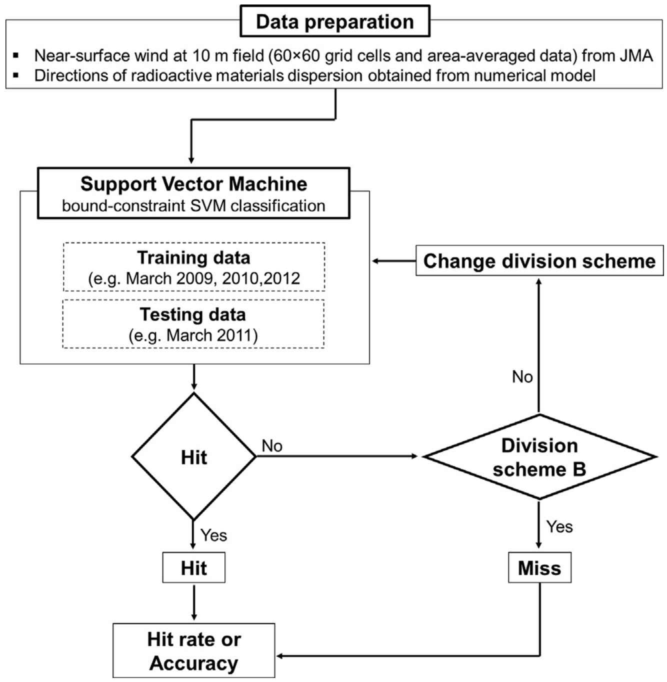

Fig. 5. Flow chart of support vector machine algorithm developed for predicting dispersion characteristics of radioactive materials.

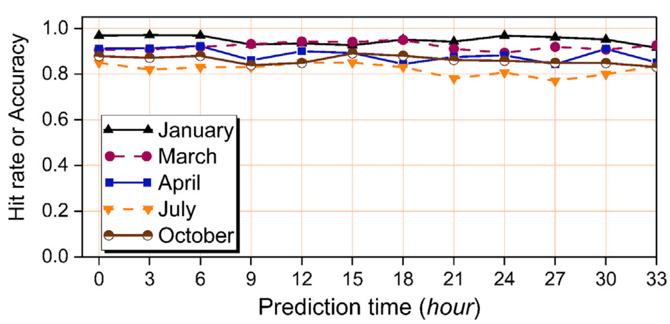

Fig. 6. Accuracy of predicted directions for dispersion of radioactive materials during different season of a year using support vector machine algorithm.

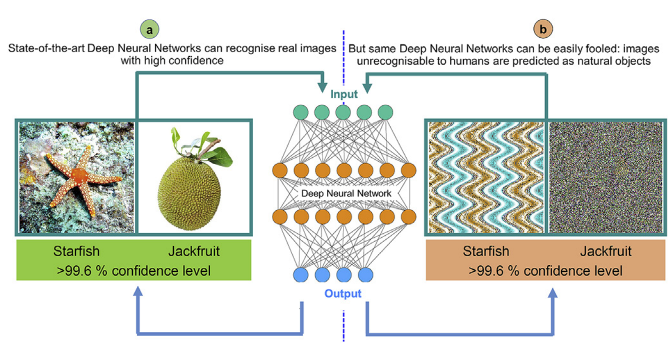

Fig. 7. Fooling of state-of-the-art deep neural networks.

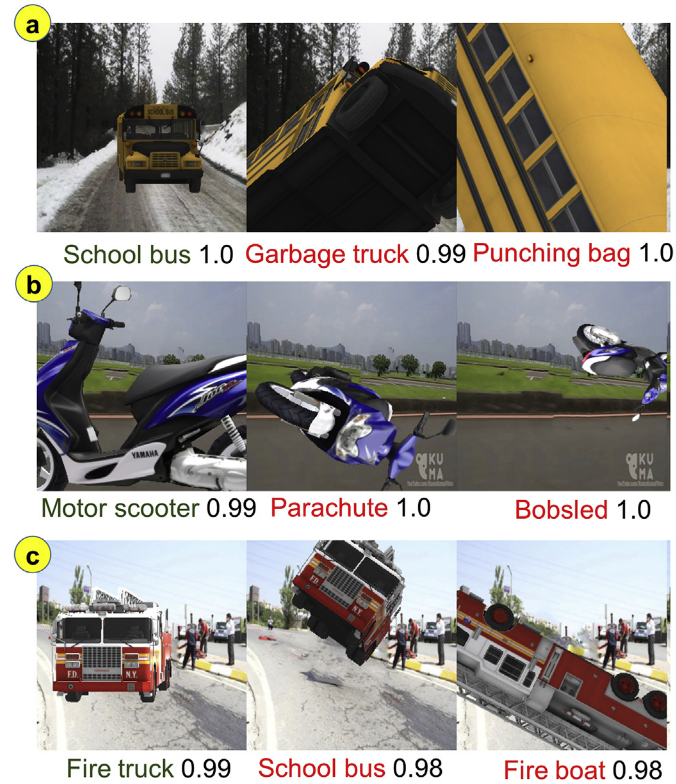

Fig. 8. Deep neural network correctly labels the canonical poses of objects but fails to recognize same image with a different pose. Each image is shown with predicted label and corresponding confidence level.

regulatory guidelines. While in initial days the focus was on developing diagnostic and condition monitoring techniques for presently operational reactors, contemporary accomplishments have focused on the employment of already developed methods for older reactors. However, there are various other intelligent systems are being developed for next generation nuclear reactors (Hines and Uhrig, 2005). Machine learning or data-driven artificial technology developed, based on simulator data, has shown satisfactory performance for a number of applications in nuclear reactor. However, lack of real operational data always poses a concern (Souza et al., 2017), especially when failure of such systems may cause huge catastrophe. There are also inconsistencies in selecting the best artificial intelligence techniques for a specific purpose, as intelligent systems developed by various researchers are based on different data set. Interlaboratory work frame or round-robin programme to develop the artificial intelligent tool for any specific purpose, based on the same data base, can be crucial in claiming the accuracy and thus the best technique.

Another major concern for implementation of artificial intelligence in nuclear industry where life of millions are virtually at stake is its black box nature. The knowledge gets baked into the networks, no real understanding of their behaviour is developed to developer or scientists. This makes artificial intelligence a tool to be sued with caution and thus transparency or understanding the behaviour of developed intelligent model is absolutely critical for many commercial applications in nuclear industry (Castelvecchi, 2016). Since the principles are hidden within the black box, the behaviour or accuracy of intelligent systems for dynamic situation which is innate characteristics of nuclear reactor cannot be trusted. Such intelligent systems are vulnerable to fooling and thus make such systems a favorable target of hackers. It was demonstrated by Nguyen et al. (2015) that deep neural network models may be easily fooled in classification of many unrecognisable images with near-certainty as members of a recognisable class tested using ImageNet. One of the examples of fooling from their findings is shown in Fig. 7. It is hypothesised that all artificial techniques based discriminative models are vulnerable to this fooling phenomenon. It raises a grave concern for the use of artificial techniques in nuclear industry as it may be fooled during accident scenarios as not respond. Recently, it was also found by Alcorn et al. (Alcorn et al., et al.) that a simple change in orientation of an object can also lead to wrong labelling of the object. In other words, just change of pose by object leads to fooling of artificial intelligent systems, as shown in Fig. 8.

5. Conclusions

Nuclear power reactors are inherently complex and technically challenging engineering system. Idea of applying computational intelligence in nuclear industry for different applications is not recent. A major concern in development of advanced artificial intelligent model for real time implementation in nuclear industry is lack of reliable database especially for transients and accident scenario. Even though artificial intelligence has made a quantum leap in recent times, its black box nature also poses a serious challenge for its implementation in nuclear industry, as it makes them prone to fooling. A need of further research in artificial intelligence focused on need of nuclear industry is required before such systems may be fully implemented.

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Artificial intelligence for the support of regulator decision making

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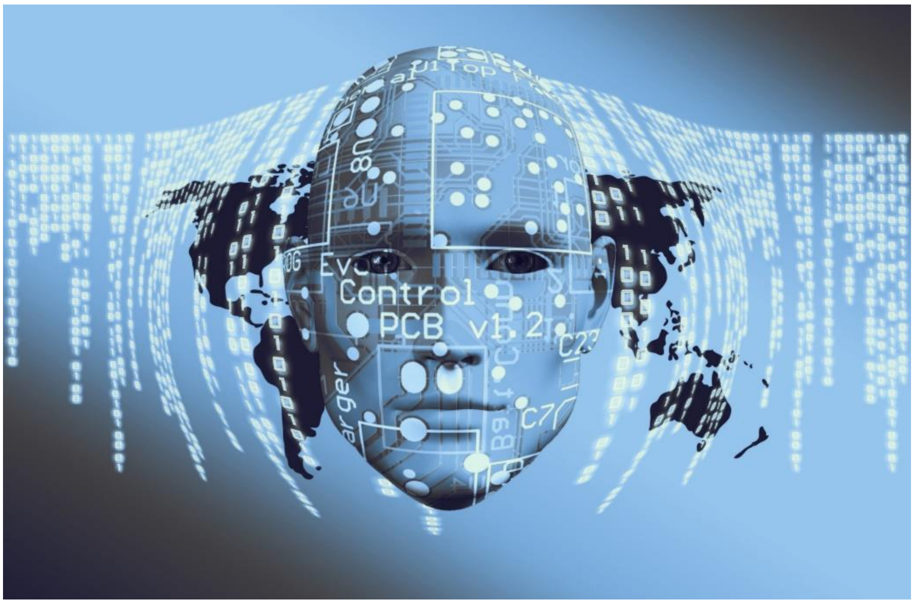

Artificial intelligence for the support of regulator decision making

Authors: Juha Kortelainen, Akhtar Zeb, Heikki Ailisto

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Summary

This study was aimed at providing views on new areas where AI could be reasonably utilised in regulatory activities in the nuclear energy domain. The goal was to review the possibilities of AI in nuclear safety research and development from different point of views, including the existing authority processes, but also chains of processes in which different stakeholders are involved. In addition, tasks, processes and activities, in which the other stakeholders could apply AI and which affect the authority and nuclear safety in general, were included.

The study contained detailed discussions with experts of different fields, both in nuclear energy sector as well as in the research and especially in the AI research sector. One small scale workshop was organised to get information about the needs and bottlenecks of the main organisations in the nuclear energy sector in Finland. In the workshop, the participants shared with others the status of applying AI in their organisation as well as their ideas of potential applications of AI and interesting fields of research. The study included a large set of background material to illustrate the landscape of the nuclear energy domain and its needs, the tasks, operations and processes of the nuclear authority, STUK, and the research and development activities of applying AI in the global nuclear energy domain.

During the process, potential large research themes as well as detailed research topics were collected to have enough data for an analysis of future research themes. From the potential research and development themes, the most promising ones are proposed for the future research projects in the next national research programme of this domain.

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Preface

The SAFIR2022 programme gave the authors a challenging task to propose research themes and topics to improve the nuclear authority operations and processes with AI in Finland. The given challenge combines two different and demanding areas, the dedicated highly specialised domain of nuclear energy and nuclear safety, including detailed legislation and regulations, and challenging technologies, and the fast evolving and extremely wide area of research in AI. The time scale in the former is years if not even decades, while in the latter it is months or weeks, if not even days. The research community in AI is global, very wide and active, and the investments in research and development are big. This is evident from the number of scientific publications within the theme, but also from the number of solutions and products that are develop both for the industrial as well as in consumer markets. As in many other similar challenges that combine technologies and solutions with working processes, the overall framework in nuclear energy and nuclear safety sector is complex. Technologies cannot be progressed without taking the operations and working processes, eventually us humans, into the loop. And the processes are hardly independent and clear, but they tend to form chains and have relations with other activities. This is also the case within the nuclear safety domain. For this work, it has required communication, thinking, learning, and eventually understanding the framework.

The process of diving into the details of the nuclear safety authority processes and, on the other hand, the possibilities of the AI technologies has been interesting and instructive. We authors thank the SAFIR2022 programme for the opportunity to go through the process, to learn new and to widen our view of new application possibilities of AI.

Espoo 15.10.2020

Authors

Cover image: Gerd Altmann, from Pixabay

Contents

Executive summary

This study was aimed at providing views on new areas where AI could be reasonably utilised in regulatory activities in the nuclear energy domain. The goal was to open the possibilities of AI in nuclear safety research and development from different point of views, including the existing authority processes, but also chains of processes in which different stakeholders are involved. In addition, tasks, processes and activities, in which the other stakeholders could apply AI and which affect the authority and nuclear safety in general, were included.

The study contained detailed discussions with experts of different fields, both in nuclear energy sector as well as in the research and especially in the AI research sector. One small scale workshop was organised to get information about the needs and bottlenecks of the main organisations in the nuclear energy sector in Finland. In the workshop, the participants shared with others the status of applying AI in their organisation as well as their ideas of potential applications of AI and interesting fields of research. The study included a large set of background material to illustrate the landscape of the nuclear energy domain and its needs, the tasks, operations and processes of the nuclear authority, STUK, and the research and development activities of applying AI in the global nuclear energy domain.

During the process, potential large research themes as well as detailed research topics were collected to have enough data for an analysis of future research themes. These are introduced briefly below. From the potential research and development themes, the most promising ones are proposed for the future research projects in the next national research programme on nuclear safety.

Main findings

Below are the main findings of the study:

- The research and development within the AI domain is very wide and active. The research volume worldwide is big, which is shown e.g. in the number of scientific publications. In addition, commercial investments in AI are remarkable, mainly due to the potential of the technologies and high business expectations.
- The prerequisites for AI application research in Finland are good. The availability of mature technologies, our good education in AI and the relatively large volume of university graduates from AI dedicated programmes, and Finland’s high quality in basic and applied research pave the way for successful research and development of AI applications.
- The operational processes within the nuclear safety domain are often chained and involve several stakeholders. Selecting the scope for studies requires thorough understanding of the authority and the other stakeholders’ processes.
- Efficient research and development in AI applications in the nuclear energy and safety domain requires combining competences and knowledge in both AI technologies and nuclear safety. This means in practice that the experts within two rather different domains need to collaborate and work together. This, on the other hand, requires common practices and common language to be efficient and fluent.

Recommendations

One of the main objectives of this study was to collect the needs and opportunities of the research focusing on using AI in nuclear energy and nuclear safety domain, especially from the authority processes point of view, and to analyse and process them into a form of research

theme proposals. Below are the main research theme proposals together with some selected more concrete research topics:

- Knowledge management and knowledge engineering:
    - *Common domain vocabularies, prerequisites for seamless interoperability of systems*: Formal definition of common concepts and terminology in the form of data models, ontologies, knowledge graphs or other general representation. This is the basis for many further research and development topics within the domain.
    - *Knowledge capture and management*: Formal capture and management of knowledge within the processes, management and utilisation of tacit, domain and engineering knowledge.
    - *Data utilisation and metadata*: Processing of lower value data into new information and knowledge. Improved utilisation of existing data and information, e.g. better data search capabilities and data organisation.
    - *AI in complexity management*: Use of graph-based data representation, utilisation of graph analysis, reasoning and inferring of information. Application of data analytics and e.g. machine learning with complex data in complex processes.
- AI in engineering design:
    - *Data analytics in engineering*: Application of data analysis and e.g. big data technologies in engineering to extract new information from data. Data-based models of systems and phenomena, application of machine learning.
    - *Hybrid methods*: Combining the data-based approach with other methods, such as deterministic models and simulation. Combining measured or sensor data with e.g. data produced with simulation, application of data analysis and other AI methods.
    - *Computational big data*: Studying systems and phenomena with computational, deterministic and other models, and data analysis. Application of large computational analysis techniques with big data and data analysis approaches.
- AI in operation, condition monitoring, and fault and anomaly detection:
    - *Operator support and training*: Use of AI in process operator support and training by applying e.g. advanced data analytics, data visualisation, and expert systems.
    - *Feature recognition from data*: Use of data analysis and machine learning in condition monitoring, and fault and anomaly detection. Recognition of features from data.
    - *Simulation enriched data*: Application of hybrid approach for machine learning in fault and anomaly detection. Representative data generation for e.g. artificial neural network training.
- Other research and development themes:
    - *Improvement of administrational and operational processes*: Application of AI technologies in various places of administrational and operational processes, taking the human aspects into account.
    - *Media and social media follow-up*: Application of natural language processing, data analytics and machine learning on media and social media data to recognise patterns and features.
    - *Overall security and cyber security*: Use of AI in security and cyber security analysis, engineering and monitoring.

1. Introduction

The idea of artificial intelligence (AI), or machine intelligence, has fascinated already the people of ancient Greece. Mechanical constructions and machines that could help people in hard labour and had abilities to think and communicate with people were already introduced by the Greek philosopher Aristotle (384–322 BCE) [1]. Since those days, numerous visionaries, science fiction writers and researchers have discussed and written about the topic. The concept of an intelligent machine took a leap with the research of Alan Turing in 1950's and by his articles about "intelligent machines" and "computing machinery and intelligence" [2]. In his work, Turing asked the fundamental and philosophical question: "Can machines think?" Since that, the development of semiconductors, electronics and computers, together with the progress in computing methods and algorithms, has been fast and has enabled the research and development of artificial intelligence to take giant steps. The concept of AI itself has also been evolving and covers nowadays a wide variety of methods and technologies. While the philosophical question of a thinking machine still remains, the practical advancements in the field have been clear.

AI has become a set of technologies that is under active application, research and development. The breakthroughs e.g. in machine vision and feature recognition have enabled fast progress in the development of autonomous vehicles, such as self-driving cars. According CB Insights [3], more than 40 corporations, including the main car manufacturers and technology providers, are having research and development activities concerning self-driving cars and related technologies. The results of applying AI technologies are already available and in use. For instance, the advanced machine learning (ML) methods make it possible to have fast but still high-quality language translation services even in real-time and in our smartphones [4].

The scientific research on AI has increased steadily and e.g. the increase in the number of publications has shown exponential features during the past five years (Figure 1). The *AI Index 2019* report [5] highlights the following aspects, among others:

- "*Between 1998 and 2018, the volume of peer-reviewed AI papers has grown by more than 300%, accounting for 3% of peer-reviewed journal publications and 9% of published conference papers.*" (Research and development)
- "*Attendance at AI conferences continues to increase significantly. In 2019, the largest, NeurIPS, expects 13,500 attendees, up 41% over 2018 and over 800% relative to 2012. Even conferences such as AAAI and CVPR are seeing annual attendance growth around 30%.*" (Conferences)
- "*In a year and a half, the time required to train a large image classification system on cloud infrastructure has fallen from about three hours in October 2017 to about 88 seconds in July, 2019. During the same period, the cost to train such a system has fallen similarly.*" (Technical Performance)
- "*Globally, investment in AI startups continues its steady ascent. From a total of $1.3B raised in 2010 to over $40.4B in 2018 (with $37.4B in 2019 as of November 4th), funding has increased at an average annual growth rate of over 48%.*" (Economy)
- "*At the graduate level, AI has rapidly become the most popular specialization among computer science PhD students in North America, with over twice as many students as the second most popular specialization (security/information assurance). In 2018, over 21% of graduating Computer Science PhDs specialize in Artificial Intelligence/Machine Learning.*" (Education)
- "*The total number of miles driven and total number of companies testing autonomous vehicles (AVs) in California has grown over seven-fold between 2015–2018. In 2018, the State of California licensed testing for over 50 companies and more than 500 AVs, which drove over 2 million miles.*" (Autonomous)

- "*There is a significant increase in AI related legislation in congressional records, committee reports, and legislative transcripts around the world.*" (Public perception)
- "*In over 3600 global news articles on ethics and AI identified between mid-2018 and mid-2019, the dominant topics are framework and guidelines on the ethical use of AI, data privacy, the use of face recognition, algorithm bias and the role of big tech.*" (Societal considerations)

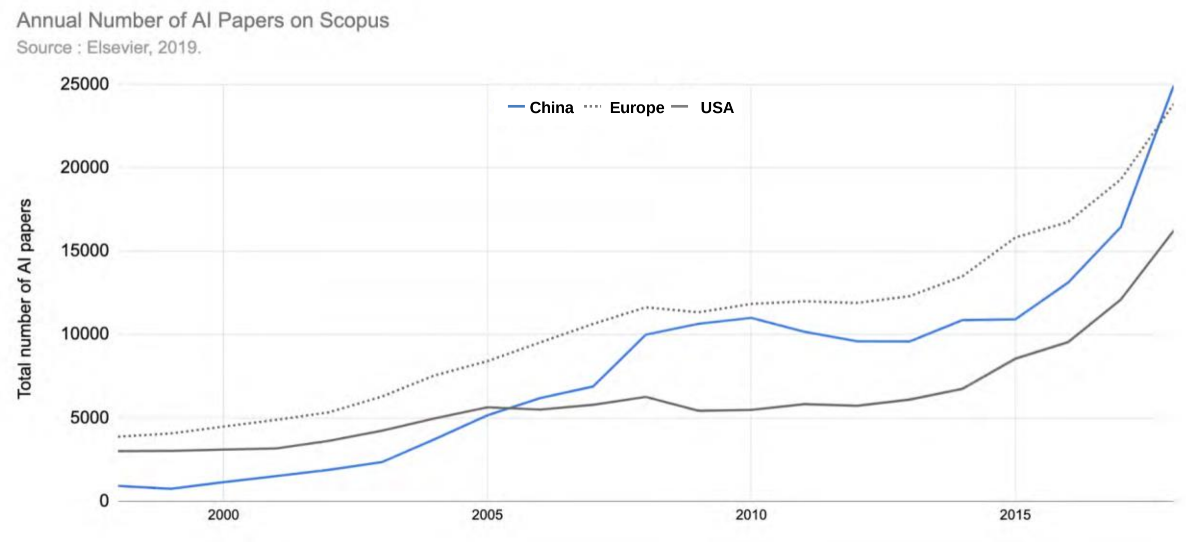

Figure 1: Number of AI related scientific papers per year on Scopus [5].

The development investments in the AI technologies and applications are remarkable, due to the high expectations in business. A market research company, Grand View Research, has analysed that the global size of the artificial intelligence market in 2019 was USD 39.9 billion and the market is estimated to grow in annual rate of 42.2% from 2020 to 2027 [6], reaching the size of USD 733.7 billion [7]. Another market research company, Gartner, has AI in many roles in their annually updated analysis of emerging technologies. In their analysis for year 2020, AI is involved in the following 11 technology trends out of 30 [8]:

- AI-assisted design
- Self-supervised learning
- Generative adversarial networks
- Adaptive ML
- Composite AI
- Generative AI
- Responsible AI
- AI augmented development
- Embedded AI
- Explainable AI
- Ontologies and graphs

At the same time, when there is a clear technology and commercialisation hype ongoing with AI and its applications, critical voices against its careless use are rising. The *AI Now* report 2019 [9] is pointing out some serious concerns about using AI:

- "*The spread of algorithmic management technology in the workplace is increasing the power asymmetry between workers and employers. AI threatens not only to disproportionately displace lower-wage earners, but also to reduce wages, job security, and other protections for those who need it most.*"
- "*Community groups, workers, journalists, and researchers – not corporate AI ethics statements and policies – have been primarily responsible for pressuring tech companies and governments to set guardrails on the use of AI.*"
- "*Efforts to regulate AI systems are underway, but they are being outpaced by government adoption of AI systems to surveil and control.*"
- "*AI systems are continuing to amplify race and gender disparities via techniques like affect recognition, which has no sound scientific basis.*"
- "*Growing investment in and development of AI has profound implications in areas ranging from climate change to the rights of healthcare patients to the future of geopolitics and inequities being reinforced in regions in the global South.*"

The European Commission has published ethical guidelines for the development and application of AI, the *Ethics Guidelines for Trustworthy AI* [10]. The guidelines list three components of trustworthy AI:

(1) "*It should be lawful, complying with all applicable laws and regulations*"

(2) "*It should be ethical, ensuring adherence to ethical principles and values*"

(3) "*It should be robust, both from a technical and social perspective since, even with good intentions, AI systems can cause unintentional harm*"

The guidelines document summarises the following key guidance:

- "*Develop, deploy and use AI systems in a way that adheres to the ethical principles of: respect for human autonomy, prevention of harm, fairness and explicability. Acknowledge and address the potential tensions between these principles.*"
- "*Pay particular attention to situations involving more vulnerable groups such as children, persons with disabilities and others that have historically been disadvantaged or are at risk of exclusion, and to situations which are characterised by asymmetries of power or information, such as between employers and workers, or between businesses and consumers.*"
- "*Acknowledge that, while bringing substantial benefits to individuals and society, AI systems also pose certain risks and may have a negative impact, including impacts which may be difficult to anticipate, identify or measure (e.g. on democracy, the rule of law and distributive justice, or on the human mind itself.) Adopt adequate measures to mitigate these risks when appropriate, and proportionately to the magnitude of the risk.*"
- "*Ensure that the development, deployment and use of AI systems meets the seven key requirements for Trustworthy AI: (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, non-discrimination and fairness, (6) environmental and societal well-being and (7) accountability.*"
- "*Consider technical and non-technical methods to ensure the implementation of those requirements.*"

- "*Foster research and innovation to help assess AI systems and to further the achievement of the requirements; disseminate results and open questions to the wider public, and systematically train a new generation of experts in AI ethics.*"
- "*Communicate, in a clear and proactive manner, information to stakeholders about the AI system's capabilities and limitations, enabling realistic expectation setting, and about the manner in which the requirements are implemented. Be transparent about the fact that they are dealing with an AI system.*"
- "*Facilitate the traceability and auditability of AI systems, particularly in critical contexts or situations.*"
- "*Involve stakeholders throughout the AI system's life cycle. Foster training and education so that all stakeholders are aware of and trained in Trustworthy AI.*"
- "*Be mindful that there might be fundamental tensions between different principles and requirements. Continuously identify, evaluate, document and communicate these trade-offs and their solutions.*"
- "*Adopt a Trustworthy AI assessment list when developing, deploying or using AI systems, and adapt it to the specific use case in which the system is being applied.*"
- "*Keep in mind that such an assessment list will never be exhaustive. Ensuring Trustworthy AI is not about ticking boxes, but about continuously identifying and implementing requirements, evaluating solutions, ensuring improved outcomes throughout the AI system's lifecycle, and involving stakeholders in this.*"

Despite the wide visibility and vivid discussion of AI in media, and the remarkable role of AI in global research, the concept itself has remained vague and difficult to concretise for a non-expert. This is mainly due to the fact that AI is not taken as one concept or technology, but a way of thinking how machines could help people in their tasks in a manner that has intelligent features. Ailisto *et al.* have made a study in which they have used the following structure how AI and the related research and development can be seen [11]:

1. Data analytics
2. Sensing and situation awareness
3. Natural language and cognition
4. Interaction with humans
5. Digital skills, interactions in work life
6. Machine learning
7. System level and systemic impact
8. Computing equipment, platforms, services and ecosystems
9. Robotics and machine automation – the physical dimension of AI
10. Ethics, moral, regulation and legislation

Based on the above, the picture that is drawn about the size and richness of the AI research and development is that it is very large, rapidly evolving and loaded with big expectations. This makes it difficult to pick up concrete research and development themes within AI in the context of nuclear energy, but, on the other hand, the number of opportunities for fast adoption of mature methods, technologies and solutions is remarkable. This lays a good basis for discussing how AI can help the regulator in decision making.

1.1 Goal and process of the study

This small study was aimed at providing views on new areas where AI could be reasonably utilised in regulatory activities in the nuclear energy domain. The goal was to find the most relevant research questions that the coming research projects will then try to find the answers. In practice, the goal was to open the possibilities of AI in nuclear safety research and development from different point of views, including the existing authority processes, but also chains of processes in which different stakeholders are involved. In addition, tasks, processes and activities, in which the other stakeholders could apply AI and which affect the authority and nuclear safety in general, were included.

The study contained detailed discussions with experts of different fields, both in nuclear energy sector as well as in the field of research and especially in AI research. The detailed discussions with STUK representatives focused on defining the main lines of the nuclear authority processes and the implementation and practices of these processes. The discussions with researchers added the potential applications of AI into the process as well as the needs, especially from the research point of view, of the nuclear domain. One small scale workshop was organised to get information about the needs and bottlenecks of the main organisations in the nuclear energy sector in Finland. In the workshop, the participants shared with others the status of applying AI in their organisation as well as their ideas of potential applications of AI and interesting fields of research. The study included a large set of background material to illustrate the landscape of the nuclear energy domain and its needs, the tasks, operations and processes of the nuclear authority, STUK, and the research and development activities of applying AI in the global nuclear energy domain. The background material included e.g. STUK operational plan documentation [12], several public studies on AI and numerous scientific publications.

During the process, potential large research themes as well as detailed research topics were collected to have enough data for an analysis of future research themes. From the potential research and development themes, the most promising ones are proposed for the future research projects in the next national research programme. In the study, the main point of view is in the regulator operations and processes, but the overall process, e.g. for a nuclear facility licensing, is taken into account, including the process phases done by the other stakeholders, such as license applicants and their partners and subcontractors. This is justified as the used methods, technologies and tools are often required to be accepted by the authority. Sharing knowledge and findings about the new technologies pave the way for their acceptance and wider application within the domain.

This SAFIR2022 programme miniproject is parallel with another miniproject “Machine learning in safety critical industry domains” (in progress while the writing of this report). Even though the topics of these two miniprojects are close to each other, the difference is in the scope. This report in hand focuses on the authority and working processes and how AI can improve them, and the report of the parallel miniproject clearly focuses on especially one method and group of technologies within the umbrella of AI, namely machine learning. The reports emphasise many common things but also complement each other.

2. AI and its elements

AI is a large concept and contains several methods, technologies and point of views. As discussed in Section 1, the research community is still struggling with the definition and discussion is ongoing both in technical and in philosophical fields. In their report, Ailisto *et al.* [11] define AI as follows: “*AI makes it possible for machines, software, systems and services to act in reasonably in relation to their task and situation*”. In his Master’s thesis, Pöntinen [13] discusses the definition of AI and after analysing other definitions, comes to a conclusion that AI is “*a combined effect of an algorithm and data that enables an apparatus or other non-living to act in a reasonable manner in relation to the task and situation*”. Furthermore, Pöntinen defines the main components of AI being algorithm(s), functional framework (such as a computer), and the utilised data. Koulu *et al.* [14] combine other definitions of AI and define it as: “*Artificial intelligence often refers to information systems that are capable of performing tasks that require human intelligence, such as visual recognition, speech recognition, or logical reasoning. Artificial intelligence finds a solution independently or partially autonomously by identifying possible patterns in the data and learning from its experiences. Artificial intelligence is not a single technology, but a combination of different methods such as machine learning and neural networks, which aim to add human-specific cognitive abilities to machines.*[1]” These rather pragmatic definitions of AI do not take a stand in a philosophical question of machine thinking, but focus more on the impression of the AI for its user, the elements that are used by the AI, and the technologies involved. The components of AI, i.e. algorithms, functional frameworks, and data, also well define the main fields of technologies that are involved in the application, development and research of AI.

2.1 Methods, technologies and technical enablers

2.1.1 Data-based AI

The research and development related to AI has had periods in which certain methods and technologies have dominated. The current ongoing wave in AI is emphasising machine learning and artificial neural networks, and can be seen as the era of data-based AI. The fast development in enabling technologies, such as computing technology, processor technology, data management and storage technologies together with remarkably lowered computing costs have enabled new applications especially in consumer markets. The big business opportunities together with the support (or clever investment) of large IT companies in open technologies have boosted the development. The fact that e.g. Google has provided a set of valuable AI technologies, such as TensorFlow [15] and Keras [16], openly available has clearly influenced the progress. This has been a remarkable asset for the research community to both develop the AI methods and technologies further but especially to apply them in efficient and agile manner. The concrete methods that are now evolving rapidly and are under active research and development are especially:

- Supervised and unsupervised machine learning methods in general
- Machine learning and deep learning technology
- Reinforcement learning
- Artificial neural networks

The applications, such as machine vision and application of feature recognition, and language processing, are leading the development due to numerous potential applications and big business potential.

2.1.2 Knowledge-based AI

A large effort to develop and progress AI in the area of knowledge engineering has been the development, definition and standardisation work of the Semantic Web technologies, mainly done by the World Wide Web Consortium, W3C. The so-called Semantic Web technologies are a stack of technologies enabling representation, management and retrieval of knowledge

[1] This is a machine translated English version of the original definition in Finnish. The text was translated with Google Translate [44] that uses AI for the translations [45].

in the Web. The technologies and related standardisation can be categorised into the following topics [17]:

Linked data: The form of information and knowledge is typically linked and networked. Concepts are built on top of and related to other concepts. The W3C standards and technologies for linked data include e.g. the Resource Description Framework (RDF) [18], the Web Ontology Language (OWL) [19] and the SPARQL query language [20]. The linked data standards and technologies build the basis for formal knowledge representation.

Vocabularies: Definition of concepts and their relations form the network of knowledge. These are done in form of common ontologies, taxonomies and other data models. The W3C standards and technologies for building vocabularies build on top of the linked data ones and contain e.g. the Web Ontology Language (OWL), Simple Knowledge Organization System (SKOS) [21] and Rule Interchange Format (RIF) [22].

Query: The SPARQL query language has been developed for the query and retrieval of data from the Semantic Web. Standardisation of the data query concept enables the development of the underlying technologies while taking care of compatibility with the other Semantic Web technologies.

Inference: The overall stack of technologies and the built-in concept of knowledge representation enable reasoning and inferring of data. This is the layer in which the intelligence comes into place.

2.1.3 Data analytics

Data analytics and data analysis, as one subarea of AI, is very large and diverse. Depending the point of view, it consists of analysis methods and techniques, but also means for data cleansing, transforming and modelling. In practical data analysis, also e.g. big data methods and technologies, and solutions and platforms for the analysis are part of the overall process. Data visualisation is involved in many AI processes and especially in data analysis and analytics. Visual data analysis and data mining are used for finding features and patterns in data by visualising it. The rich offering and competition in cloud services have made data storage, computing resources, and data analytics software and algorithms available for anyone in decent price. The big cloud service providers, such as Amazon AWS, Google Cloud and Microsoft Azure, provide a wide spectrum of data analytics and machine learning tools in their cloud services. The services combine easy access to large amount of data with scalable computing resources. In the open source field, Python is a dominating platform in many computing areas, including data analytics and machine learning. All these are great resources for open research but may be challenging for safety and security centric domains, such as the nuclear energy domain.

2.1.4 Autonomous systems

Autonomous systems is a field of technology that utilise many AI technologies and develop them further. Autonomous systems combine sensing and the ability to perform tasks independent of human operation in possibly changing and unspecified conditions. This requires some kind of machine cognition. The levels of autonomy in systems have been defined studied in research and they have become popularised by the media concerning the development of self-driving cars. The Society of Automotive Engineers, SAE, has defined the six levels of driving automation for vehicles [23], [24]:

- Level 0: The system provides information and warnings and momentary assistance. No automation, a support feature.
- Level 1: The system provides steering or braking/acceleration support for the driver. Driver assistance, a support feature.

- Level 2: The system provides steering and braking/acceleration support for the driver. Partial driving automation, a support feature.
- Level 3: The system can drive the vehicle in limited conditions, such as traffic jams. The driver must take control when the system requests it. Conditional driving automation, an automated driving feature.
- Level 4: The system can drive the vehicle in local conditions; e.g. a local driverless taxi or a bus. High driving automation, an automated driving feature.
- Level 5: The system can drive the vehicle in all conditions; a fully autonomous vehicle. Full driving automation, an automated driving feature.

Robotics and autonomous vehicles are concrete examples of the theme, but the principles can be applied to other areas of application, even without the physical dimension.

2.1.5 Natural language processing

Natural language processing is a well-established area of AI and it provides mature technologies and methods for many applications. Machine translation is one of the big topics and it is widely used in e.g. consumer services and solutions, such as in many applications in smart phones and language translation services that are available in the Internet. Natural language processing is also an important enabler in other fields of AI, e.g. in knowledge extraction and feature recognition from written text or speech.

2.2 Competences and resources, training and education

The competence level in Finland is good what comes to AI and related technologies. The Coursera Global Skills Index 2020 [25] lists Finland globally number five in the set of technology trending skills of C (programming language), artificial intelligence, JavaScript, Web development, user experience development, cybersecurity, convolutional neural network, cloud computing, Internet of Things, and application programming interface.

AI in different forms is well present in the university and applied university education in Finland as the Finnish universities offer 40 education programs in AI on Masters level, 19 on Masters and Bachelor level, 3 Doctoral programs, and 26 programs in universities of applied sciences. Several hundred students graduate from AI programs yearly, while the number of doctoral thesis on AI topics is several tens. There are more than 250 individual AI courses offered by the Finnish universities and 6300 students take at least one of these courses every year. [26]

AI is one of the most popular topics taken as on-line courses. Many software engineers and other experts have learned AI skills with online courses, which should be noted in addition to formal training, even though these courses are not recorded in national databases as traditional university courses. One of the most popular AI courses, Elements of AI, is being offered by the University of Helsinki and Reaktror [2].

The amount of formal and informal AI education means that competent resources become available for service and solution provider, their customers, and companies, which develop AI-based solutions or embed them into their other solutions. However, the demand for AI experts is also growing rapidly, so we may see at least times a mismatch between offering and demand. Brain drain or influx of foreign experts also influences the situation.

Research on AI is on comparatively good level in Finland. The quality[3] of Finnish AI research is on par with the US, UK and Germany but behind topmost countries Israel, Singapore and

[2] The website of on-line course Elements of AI https://www.elementsofai.com/fi/
[3] Quality of research is here defined as the share of publications in top-tier journals of all publications.

Hong Kong [11], [26]. Naturally, Finland is not among the leading nations in the number of AI publications. When compared to the other Nordic countries, Finland ranks the second after Sweden in the quantity of scientific publications [11] and the first in their quality. The Academy of Finland has granted the Finnish Center for Artificial Intelligence, FCAI[4], a flagship status, which means that the area has been recognised as one of the six most competitive centres of excellence in research in Finland.

3. Authority and systems engineering processes

3.1 Analysis of the authority processes

The main processes of the nuclear authority, STUK, in Finland were discussed together with the representatives of STUK and the processes were studied from the provided operational plan documentation [12]. The level of details of studying the operational processes was to understand the volume and impact of the main processes and their tasks to the overall efficiency of nuclear safety assessment. The goal was to find bottlenecks, trends and patterns in the processes where AI could improve the process, taking into account the main stakeholders involved. From the tasks and duties of STUK, the following ones were identified the most important:

- Regulation and rule setting
- Oversight, including licensing, authorisation, review and assessment, inspection and enforcement
- Media follow-up and media relations

The first two involve communication between the stakeholders and, in many places, they have clear systems engineering features. The tasks of regulation and rule setting can be compared to requirements setting in the systems engineering context. Many tasks of oversight can be compared to requirements verification and validation. All these in a large and complex systems engineering context require continuous communication and information exchange, both with formal documents and structured design artefacts and with informal manners, such as emails. The obvious common factors in this category are complexity management, improvement of operational efficiency, and especially ensuring nuclear safety in every which way. The key elements of this category are design and planning, assessment and evaluation, verification and validation, and traceability and documentation. The nature of processes and information within this category is that it is linked and dependent, complex and mainly formal, and it must be traceable and well documented.

The second identified main task, oversight, include also supervision and control of the engineering design and plant implementation processes, operation of nuclear facilities, and all the related aspects, such as technical details and requirement accordance, but also organisational aspects, such as safety culture and practical organisational atmosphere in the supervised organisations. The obvious common factors are to ensure nuclear safety, the fulfilment of regulations, and the identification of any signs and signals of potential issues. The elements in this category are monitoring, follow-up, control, and communication. The nature of processes and information is more informal than in the first category, including e.g. unannounced inspection visits to nuclear facilities, identification of details in the way the facilities are operated and the way the facility personnel is acting and behaving. The nature of collected information is heterogeneous, unstructured, and it may be based on subjective observation.

[4] The website of FCAI: https://fcai.fi/

The third identified category is related to public communication and media. It includes the follow of public opinion and discussion in media and social media of e.g. common attitude towards nuclear and radiation safety. One of the roles of STUK is to provide objective public information based on its expertise in nuclear safety and by that improve the overall nuclear and radiation safety in Finland. This can be done e.g. by proving information about the risks of radon, the risks of UV radiation, and how to prevent them. Following the public discussion and public opinion, STUK is able to target the actions and, if necessary, take part of the ongoing public debate.

Authority processes and other stakeholder processes often form a chain. An example of this is the preparation or updating of the regulatory guides on nuclear safety and security (YVL) [27], which involves formulation and assessment of requirements and their evaluation and validation. This is a process that is implemented by STUK and it involves typical requirements engineering features, among others. The concrete outcome of this regulation work, when the preparation or updating has been done, are the YVL guide documents that define the guidelines and concrete requirements. The YVL guides are currently provide in the form of prose as PDF documents and in table format (Microsoft Excel, not all of the guides).

When e.g. a power company plans to apply a license to start designing a new nuclear facility, the set regulations, in the form of the YVL guides and other regulatory requirements, step in the process. The set authority requirements for the facility need to be analysed, organised and categorised to build a view of the meaning and dependencies for the design work and the design outcome. In practice, the work starts from analysing and interpreting the documentation in prose, which requires remarkable time as there is a large number of individual requirements. As the planning and design work for applying the license continues, it requires continuous communication between the license applicant and the authority, and eventually the application, together with required design and other artefacts, are ready and the application is filed. Typically, this material contains large amount of documentation in prose, which again has to be analysed, assessed and evaluated by the authority. The application phase may contain several iterations before the decision about the license.

The example illustrates how the different, apparently independent, processes form a chain where the same information is transformed from one presentation to another possibly several times. This example does not claim that the way how things are done is not justified and meaningful, but it just points out that the overall process is more complex and involves more stakeholders than what is obvious from one specified process and one stakeholder point of view. A similar kind of example can be illustrated for oversight, which requires large amount of communication and tracing of requirements, documents and other artefacts. If the process is observed and optimised only from one stakeholder point of view, the overall benefit will most likely be only partial.

3.2 Systems engineering processes

Even though this study is about using AI in nuclear authority processes, the role of systems engineering needs to be taken into account. The ISO standard of systems and software engineering – system life cycle processes [28] defines the concept of systems engineering as an "*interdisciplinary approach and means to enable the realisation of successful systems*". On the other hand, the Merriam-Webster dictionary defines the word system e.g. as follows [29]:

- "*a regularly interacting or interdependent group of items forming a unified whole*"
- "*a group of devices or artificial objects or an organization forming a network especially for distributing something or serving a common purpose*"
- "*an organized set of doctrines, ideas, or principles usually intended to explain the arrangement or working of a systematic whole*"

Referring to the discussion in the previous section, the boundaries of the system can be set in many ways. The system can be e.g. a nuclear facility and the related operations, or it can be set to cover the overall safety in the nuclear energy domain. The same general challenges and concepts, and most of the common means to solve the systems engineering challenges apply. One of the main elements in systems engineering is complexity, i.e. the complexity of the target system (technical complexity), complexity of phenomena involved (e.g. physical phenomena), complexity in operational processes, and complexity in data and information involved, just to name some. The concept of systems engineering and the management of systems life cycle form the framework and context for applying AI in nuclear authority processes.

4. Literature study on research themes

The use of AI in nuclear energy domain is globally an active research topic. To have an overview of the nature of the research, a small scale scientific literature review was done. The search for scientific publications was done using the following search terms: “nuclear energy”, “nuclear power”, “nuclear safety”, “artificial intelligence”, “machine learning”, “natural language processing”, “NLP”, “nuclear”, “systems engineering”, “requirement”, and “requirements engineering”. As the research in the general field of AI is very active, also the research focusing on AI in the nuclear energy domain is wide and e.g. a search in the Google Scholar service with the combined search terms “nuclear energy” and “artificial intelligence” produces about 10700 results. Below are some examples of the research topics based on the scientific publications:

- [30]: In his literature review, Suman (2020) discussed the applications of AI in nuclear industry. The review contains 112 references to scientific research publications. The author categorised the various AI techniques, their applications and researchers’ findings into:
    - Operation of nuclear power plant
    - Fuel management
    - Fault diagnosis in nuclear power plant
    - Identification of nuclear power plant transients
    - Identification of accident scenario
    - Miscellaneous interesting applications

  The author concluded that although AI has many applications in the nuclear industry, nevertheless, its black box nature is still a major challenge for wider implementation, requiring more research.

- [31]: In their literature study, Gomez-Fernandez *et al.* (2019) discussed the fundamentals of AI and the state of development of learning-based methods in nuclear science and engineering to identify the risks and opportunities of such methods. The literature review contains 233 references to scientific research publications. The applications of machine learning to the field of nuclear science and associated engineering were categorised into:
    - Plant health and management approaches
    - Radiation protection
    - Optimisation

- [32]: Myllynen (2019) developed a requirements categorisation algorithm by utilising the deep supervised learning method. The aim of the natural language processing algorithm was to categorise nuclear power industry specific requirements into predefined categories. The algorithm was applied for the categorisation of requirements from the

YVL Guides issued by the Finnish Radiation and Nuclear Safety Authority (STUK). The results indicate that the current technology of deep supervised learning and natural language processing are sufficient to be utilised in the requirements classification tasks.

- [33]: Meta-models are approximations of more complex computer models, and they provide a feasible alternative to the simplifications required when computational burden limits the number of high fidelity model runs that can be performed. Worrell *et al.* (2019) discussed the application of machine learning in fire probabilistic safety assessments of nuclear power plants. A k-nearest neighbour (kNN) meta-model was found to be more suitable compared with a simpler model chosen for computation feasibility.

- [34]: Fernandez *et al.* (2017) investigated the application of machine learning for predicting system behaviour in the nuclear engineering domain. Artificial neural networks were created for the behaviour prediction of the Oregon State University's Multi-Application Small Light Water Reactor integrated test facility under various core powers and a loss-of-feedwater event scenarios. The neural network with backpropagation algorithm was trained in the supervised learning process with labelled data from 58 different sensors. The predictions of neural networks were found comparable with the raw sensor data without any post-processing. Thus, artificial neural networks are very useful in providing technical data that can be used by the decision makers to take appropriate actions, identify safety issues, or provide an intelligent system with the potential of using pattern recognition for reactor accident identification and classification.

- [35]: Zeng *et al.* (2017) proposed a machine learning based system performance prediction model in order to support the development of autonomous control system for small reactors, such as the Transportable Fluoride-salt-cooled High-Temperature Reactor. The prediction model consists of a reactor physics model and a thermal-hydraulic model, and was constructed using the support vector regression method. The training data for the model was taken from the ID reactor system model. It was found that the model performed well in predicting the core behaviour and in recognising various transient parameters (e.g. reactivity insertion timing and rate).

- [36]: The safer operation of nuclear power plants requires accurate classification of multiclass transients. Prusty *et al.* (2015) conducted a comparative study on the performance of various multiclass supervised machine learning methods, such as k-nearest algorithm, support vector machine algorithm, and artificial neural networks. It was concluded that the Bayesian regularisation backpropagation artificial neural network is the best for transient classification in safety critical systems in nuclear power plants.

- [37]: In the pressurised water reactor nuclear power plants, the main component responsible for controlling pressure in the primary loops is the pressuriser. Oliveira *et al.* (2013) used artificial neural networks for modelling the pressuriser pressure model, as well as developed fuzzy controllers for this model in order to compare their performance with conventional PID controllers. Data from a 2785 MWth Westinghouse 3-loop pressurised water reactor simulator was used to test both the pressuriser artificial neural network model and the fuzzy controllers. The authors concluded that the results of pressuriser artificial neural network model are similar with those of the simulated power plant pressuriser, and the fuzzy controllers performed better than the conventional PID controllers.

- [38]: The accurate estimation of local power density at the hottest part of a nuclear reactor core is necessary to avoid melting of the fuel rod in a nuclear core. Bae *et al.* (2009) investigated the application of support vector machines for predicting the power peaking factor, which is the highest local power density to the average power density in a reactor core. The support vector machine regression models were provided with numerous measured signals of the coolant system. The predicted values were found accurate enough and it was recommended to utilise support vector machine regression models for core protection and monitoring that uses power peaking factors.

- [39]: Santosh *et al.* (2008) discussed the application of artificial neural networks in developing a diagnostic system for the identification of accident scenarios in pressurised heavy water reactors. The operator support system was developed using artificial neural network that diagnoses the transients based on reactor process parameters. In the study, several break scenarios of large break loss of coolant accident with and without the emergency core cooling system were analysed. The results obtained were found satisfactory and the artificial neural network were incorporated in the operator support system for accident management.

- [40]: The operation of nuclear power plants involves a number a transients, due to components failure, malfunctioning of process systems, plant accident scenario, or any other disturbances, resulting in abnormal plant conditions. In such undesired situations, the plant operators are required to quickly diagnose faults and take corrective actions as soon as possible. In order to assist the plant operators, Santosh *et al.* (2007) investigated the application of neural network algorithms for identifying such transients at the earliest stages of their developments. Several algorithms were trained and tested for a number of abnormal events of a typical nuclear power plant. The study concluded that the resilient-back propagation algorithm performs well in the selected range of anomalous operating conditions, and was, therefore, adopted in the development of operator support system.

- [41]: Nabeshima *et al.* (1997) studied the application of artificial neural networks for detecting anomalies in the operation of nuclear power plants. The plant was modelled using a three-layered auto-associative artificial neural network, which is good in detecting unknown plant conditions. Using the backpropagation algorithm, the artificial neural network was trained by typical operational data off-line during the initial learning, and then the adaptive learning was carried out in real-time. The methodology applied was to detect the anomaly with deviation between the process signals measured from the actual plant and the corresponding output signals from the plant model created with artificial neural networks. The test results showed that this plant monitoring system is successful in detecting the symptoms of small anomalies in real-time over the wide power range including start-up, shut-down and steady state operations.

- [42]: Reifman (1997) discussed artificial intelligence tools, methods and approaches proposed by various researchers for the detection and identification of components faults in the nuclear industry. The diagnostic systems are based on several AI techniques, such as expert systems, artificial neural networks, numerical simulation, as well as hybrid approach (i.e. combination of these). Such decision-support systems are useful in the analysis of off-normal plant conditions, including identification of loss-of-coolant accidents resulting from small pipe breaks at the inlet or outlet of a steam generator, obtaining information the sizes of pipe breaks, and classification of discrepancy between measured plant parameters and expected behaviour calculated by reference simulation models.

- [43]: The operation of nuclear power plants involves many process parameters and system interactions that the operators have to handle in routine as well as emergency situations. The difficulty of managing such parameters depends on the available facility for conversion of raw data into meaningful information and knowledge. In order to assist the plant operators, the applications of AI technologies, especially the expert systems, have been proposed to improve the safety and reliability of nuclear power plants. Uhrig (1988) discussed the work of various researchers in developing expert systems for multiple purposes, such as classification of emergency situations, tracking system for emergency operating procedures, generating a list of necessary refuelling moves for a reactor, analysing the limiting conditions of operation and technical specification in a nuclear power plant, valve maintenance planning, and so forth. Expert systems assist operators in smooth operations and better management of nuclear power plants.

The main trends in the research are diagnostics, fault and anomaly detection, system behaviour prediction and surrogate or meta-models. As the amount and availability of sensor data, together with digital engineering design data, is expected to increase, the emphasis of the research and development in the nuclear domain would naturally be in data intensive topics and in the use of AI in feature recognition type of applications.

5. AI research needs and trends in nuclear energy sector

Within this study, the research topics and needs were collected throughout the process and analysed to find potential themes for research in the SAFIR context. This was done in all the discussions with different parties and especially in a workshop organised to collect the needs and ideas for research, and to present already done research and development activities in using AI in the nuclear energy sector. The list of research topics contained in total 56 titles in 14 main categories. This can be seen as raw material for further elaboration of larger research themes. The categories (the main category underlined) are:

- <u>Condition monitoring</u>, anomaly and fault detection, system behaviour prediction:
- <u>Data analysis</u>, complexity management, data visualisation, dependency analysis, information management, natural language processing, operational processes:
- <u>Data management</u>, data analysis, information management, operational processes:
- <u>Data security</u>, cyber security, data analysis:
- <u>Data strategy</u>, definition work:
- <u>Material engineering</u>, data modelling:
- <u>Natural language processing</u>, data analysis:
- <u>Operator support</u>, diagnostics and decision making, expert system and data analysis:
- <u>Operational process management</u>, data analysis, dependency analysis, process automation:
- <u>Regulation</u>, process automation, process management, systems engineering:
- <u>Simulation</u>, control systems, surrogate modelling, system behaviour prediction, systems engineering:
- <u>Systems engineering</u>, data management, data transformation, model-based systems engineering, requirements, semantics, validation:
- <u>Uncertainty quantification</u>, system reliability:
- General themes in digitalisation:

The research theme categories and their descriptions are presented with more details in Appendix A. The research theme proposals, based on the list above, are discussed in more detail in the next section.

5.1 Proposals of research themes

In this sections, a small set of proposals for larger research themes of AI in nuclear energy domain are presented, based on the numerous discussions, available research publications and the analysis of this material. Below are proposals that involve the use of AI in the nuclear energy domain processes of the nuclear authority, other stakeholders, or both. The proposals take into account the general research and competence development approach of the SAFIR programme. The proposals include topics building prerequisites for further AI related research as well as concrete topics for applying AI for different purposes. A summary of the research theme proposals is presented in the Executive summary on page 4 and in Appendix B.

5.1.1 Knowledge management and knowledge engineering

Common domain vocabularies, prerequisites for seamless interoperability of systems: One theme that raised in the discussions during this study was the need to define and maintain common vocabulary, a set of terms and concepts, their definitions and relations. This is the basis for efficient communication between the stakeholders, whether it is about research on AI applications or something else. In some fields of AI, namely knowledge engineering and natural language processing, formal vocabularies, in form of data models, knowledge graphs or ontologies, are the basis for building advanced solutions. In knowledge engineering, formal knowledge representations is based on building new knowledge on top of existing concepts by linking the concepts and defining the features of their relations. In natural language processing, the existing formal definitions of concepts enable more accurate and more efficient processing of natural language, such as documents and speech. The direct added value of the research and development is the improved communication between the stakeholders, easier joining of new experts from outside the nuclear safety research domain. The formal definition of common concepts and terms can be seen the foundation of e.g. knowledge engineering and natural language processing, which further can improve or even automate the transformation of information in the processes. From the business opportunities point of view, this can decrease the efforts needed to transfer Finnish national knowledge and know-how in nuclear safety and systems engineering of nuclear solutions to international and global services. Developing abilities to process information language independently makes scaling solutions and technologies from one market to others easier.

Knowledge capture and management: Information and knowledge management in authority and systems engineering processes was identified as one of the grand challenges. Formal management of informal knowledge, or tacit knowledge, has been found a necessity to remarkably improve the efficiency and productivity of processes. On the other hand, technical management of informal knowledge is very challenging and, as such, a large and difficult research topic. The research in knowledge engineering is already matured and solutions, both research as well as commercial ones, for e.g. linked data management and knowledge reasoning exist. For practical applications of knowledge engineering in e.g. authority and systems engineering processes, the bottleneck of getting the knowledge into knowledge management systems is still an issue and a fruitful place for research. This could include combining knowledge engineering and management approach (in research, sometimes called as classical AI) with the latest feature recognition and data and information classification methods (in research, sometimes called as modern AI). The former providing means to collect, manage and use the knowledge that has been captured, extracted and recognised by the means of the latter. The added value comes from better utilisation of existing knowledge, generation and collection of new knowledge (e.g. by the means of data analytics), and the automation of the knowledge extraction and management process. The vision could be a modern expert system or framework that automates the use of information and knowledge in complex processes.

Data utilisation and metadata: The extremely fast development of information and computer technology has turned the situation of not having enough data for efficient decision making to opposite, i.e. the amount and availability of data is hindering the finding of useful information. One of the attempts to solve this issue is to improve data processing to turn relatively low value data into higher value information and further to knowledge. This has been briefly introduced above with the theme of knowledge management and capture. Another way to improve the value of data is to make the relevant data more easily available. Means for this are e.g. better organisation of data and improved data search capabilities. Reorganising of already existing unorganised and large set of data is a potential application of AI. Improving data search and finding relevant data can be done by providing data about the content of data, i.e. metadata. A potential application for AI is to automate the metadata generation to improve data accessibility.

AI in complexity management: Complexity and its management was a theme that raised in many places during this study. Both the operational processes, e.g. regulation development and management, and the systems engineering of a nuclear facility licensing and design, are very complex. In addition to knowledge representation, knowledge graphs and linked data can be used for managing information. An example of this is the use of semantic technologies in requirements engineering. A simple search in Google Scholar service with search terms "requirements engineering" and "semantic" results in about 37.600 search results of scientific publications (patents and direct citations excluded). The rich field of research publications provides a good starting point for applied and domain specific research. This theme is benefitting from the generation of common vocabularies and defining of commonly used concepts and terms, discussed above in theme common domain vocabularies. Ability to enrich the linked data with restrictions, rules and constraints, and using formal reasoning and inferring enables automation of information consistency checking and validation. These are the elements to define, collect, manage and utilise information and knowledge in formal systems, and to automate the process. The applicability of these methods and tools is general and the same methods and technologies can be used for operation process management, information management automation and intelligent information validation as well as in complex systems engineering tasks.

5.1.2 AI in engineering design

The research themes below are mainly focused on systems engineering and technical design, and do not directly influence the authority processes. The justification of introducing them here is that the methods need to be thoroughly studied, developed and validated to be in accordance with the requirements of the authority. Involving these into the scope of e.g. the SAFIR programme makes them better known and accepted by all the stakeholders within the nuclear domain.

Data analytics in engineering: The use of AI in engineering design and the related research is growing fast. AI methods and technologies provide new opportunities especially when there is large amount of data available, but the relevant information is hidden into the data. The use of data analysis and e.g. big data technologies is already common in research and development. Methods and solutions for this are mature and well available. Application examples are e.g. the use of condition monitoring or sensor data in the development of new solutions. The existing data can be used e.g. for defining more reliable loading conditions for new systems and structures. The increasing availability of raw data from systems and the advanced data storage and management systems together with data analytics algorithms and tools have made this fast and feasible for practically any organisation.

Another common topic of using AI in engineering design is to model e.g. a system, structure or a phenomenon based on the available data. The data-based model of the target can then be used in many ways, e.g. in research and development to represent the target in analyses or as a component of a system (e.g. in model predictive control). Especially applications, in which good computing performance is required, such as real-time control or advanced mathematical model-based optimisation, the data-based models can be very efficient. One concrete application of data-based models is the use of surrogate models of computational model containing complex physics. The data-based surrogate model can be created with machine learning, it can contain non-linear features and it can be used in transient time-dependent applications.

Hybrid methods: An area of increasing interest is the use of hybrid methods, which combine experimental, measured or sensor data with e.g. deterministic models. Instead of using experimental data for validating the deterministic models, the data, or the model that is based on the data, is part of the overall deterministic model. The motivation for this is the increasing availability of experimental, measured and sensor data from systems.

Computational big data: Another approach of hybrid methods is to combine deterministic methods and data analytics. The availability of large computing resources and the fast development in computing technologies and computational methods have led to a situation, where producing numerical data with computer simulation is relatively easy and fast. As discussed already above in theme data utilisation and metadata, the increasing amount of raw data is hindering the finding of valuable information that is hidden into the data. Application of data analytics, and especially the use of exploratory data analytics methods, can extract new information out of data that is produced with deterministic simulations. This could be done in practice by running large computational studies, such as different types of design of experiments, with deterministic models, collecting the results data (raw data) into one data mass, and applying different data analysis and data mining algorithms to the data. The continuous increase in computing and data storage and ability to automate both the data production and data analysis is making this approach increasing interesting. The approach could be called as the computational big data method.

5.1.3 AI in operation, condition monitoring, and fault and anomaly detection

Operator support and training: The theme of processing large amount of data into valuable and useful information is repeated within this context. In plant operation, the operator should get only valuable and useful information. Data analytics and data visualisation are means to improve the value of data and ways to turn data into useful information. Another aspect is the research in how the operators do their work and how it can be improved. AI provides new means for conducting the human-system interaction, such as real-time feature recognition from video or other media formats, use of data analytics to measured signals, such as measurement of human pulse or breathing. This theme can improve our understanding of the human behaviour in stressful situations and its influence on our ability for decision making. Another direction could be to develop advanced operator support systems or expert systems that help the operators to improve their work reliability and to improve their productivity. The raising interest in the concept of small reactor units also initiates the need for remote operation of plants and operation of multiple plants by the same operators.

Feature recognition from data: One of the most common applications of the modern AI technologies is to use machine learning and e.g. artificial neural networks for feature recognition from data. The use of these data-based models of the target enables fast recognition of features, thus, enabling even real-time applications of these methods. Examples of applications requiring fast algorithms are e.g. feature recognition in live video, used in autonomous systems for navigation. Another application is system condition monitoring, and fault and anomaly detection. This has been a topic in many studies that were found in the literature review, discussed in Section 4. Like in many other research theme proposals above, one of the main motivations for this is the availability of measured and sensor data from systems and the fast evolvement of data analysis and feature recognition technologies and their implementations. This theme applies mainly the plant owner and operators, but like in theme AI in engineering design, these methods and technologies need to be thoroughly studied, developed and validated, and made commonly known in the nuclear energy domain before they can be accepted into the palette of common methods.

Simulation enriched data: The use of data-based approach in fault and anomaly detection is sometimes challenging due to the lack of measured data of the faulty conditions or system anomalies. E.g. the use of machine learning requires representative data of the features to be recognised. If the feature is a system fault, the training process of the data-based model requires data of that kind of a faulty condition. Otherwise this approach can be used for detecting that the system is not behaving in normal manner, but any reliable recognition of the exact type of the fault or anomaly is difficult to make. An approach to overcome the problem is to use simulated data of faulty situations or anomalies for the training of the data-based model. If there is some measured data of the faults of the real system, this data can be used for fine tuning the data-based model and to validate the model. This kind of an approach can utilise the existing design models of the systems, and, thus, is relatively straightforward to apply. The simulation-based data generation, the machine learning and especially the validation of the model requires still remarkable further development and research.

5.1.4 Other research and development themes

Improvement of administrational and operational processes: There are obviously numerous places, in which AI can be used for improving administrational and operational processes of organisations. Complexity management can as well be applied to formal authority processes, such as for evaluation of a nuclear facility license application or regulatory supervision and control of operating plants. Finding the bottlenecks and understanding the overall processes, their subsets and human’s role is essential. Organising data, defining metadata for the data, improving data utilisation by the means of e.g. making it easier to find it are examples of research and development themes in this category.

Media and social media follow-up: AI is widely used in media and social media analysis. The same principles as in feature recognition of other kind of data can be used for recognising e.g. phrases, related concepts and other patterns in the information flow in media and social media. This research theme is in the outer edge of the nuclear safety research of the SAFIR programme, but can be seen as a valid topic from the security point of view. In addition, the technologies and solutions in this theme are already relatively mature and can be applied with only modest effort.

Overall security and cyber security: Security aspects in the nuclear energy domain require a slightly different point of view and attitude for research. The phenomena involved are not physical or deterministic, and the use of data has to be thought from different point of view. Still, the same principles as above of applying AI methods and technologies apply. AI methods are already applied in cyber security and there are many interesting areas where the research and development can be taken further. Topics can include e.g. security analyses, security engineering and monitoring, and application of AI in these areas.

5.2 Features of basic and applied research of AI applications

Efficient and successful research and development of approaches that combine general methods and technologies with needs and processes of a dedicated domain requires integration of knowledge, know-how and competences from several sectors. It is rare that the best knowledge and know-how exist within the same person, but usually the best experts for domain specific topics come from within the domain, and the best experts for general technologies come from outside the domain. This is the case with the state-of-the-art in nuclear safety and in AI. AI, as a general, domain independent concept and a set of technologies, is progressed in many application fields and by method experts that are not dedicated to any specific domain.

When applying AI e.g. in nuclear domain, the experts of nuclear energy domain and method experts of AI need to work hand in hand to successfully study and develop new applications. One of the challenges is the common understanding and, in practice, the common terminology and even a common language to share the knowledge. The networked way of conducting research and development does not come automatically, but it requires determined building of collaboration and prerequisites. In practice, it requires continuous communication and co-learning.

The special nature of the nuclear safety domain, including highly specialised technologies, strong role of regulation, and long spans and life cycles, requires the experts outside of the domain to learn and comprehend it before the collaboration is efficient and fruitful. Starting as soon as possible the collaboration between the domain and method experts, building the networks between different research communities ensures that the research of these topics within the nuclear domain is efficient and impactful.

The trust in technology in general and especially in AI comes up in public debate and in formal studies. The unfortunate and dramatic accidents in the development of self-driving vehicles are cut out for increasing mistrust in AI, and for justified reason. There are many reasons for the mistrust, such as lack of understanding. This hinders the adoption of AI solutions into practice in consumer markets as well as in industry. Research, sharing information and controlled experimentation are examples of ways to lower the mistrust and accelerate the process for new innovations.

The characteristic feature of research is that it cannot be fully predictable. When dealing with things that are not known beforehand, one cannot prepare for what may come up during the journey. In applied research, another characteristic feature is that the solutions or even innovations are often creative and the solution to a problem may come from totally unpredicted direction. To enable this creativity, the needs for new solutions, i.e. the motivation, and the domain specific boundaries and restrictions should be defined well and communicated clearly, but, at the same time, the paths to the solutions should be left open. A researcher with open mind to solutions is, in the best occasion, creative and innovative, and works most efficiently when certain freedom is provided. Finding the balance between the target and boundary setting, and freedom is difficult but worth trying.

6. Conclusions

The domain of artificial intelligence is wide, deep and rich, what comes to research, development, applications, methods and technologies. Already the analysis of the general status of AI development is very challenging and it is becoming increasingly difficult as the pace and volume of development continues to increase. While writing this report, new innovations in AI are introduced, existing methods and technologies are progressing and new players are coming to the field. The best approach to get added value is joining the flow by learning new, experimenting with possibilities, and networking with the best minds and organisations.

The nature of efficiently developing and applying AI technologies is collaboration and networking. As in many other current and recent technology hypes, the applications of AI integrate technologies and competences from several fields with the understanding of the topic in hands and its context. This is clearly the case with AI applications in the nuclear energy domain and in the processes of the authority. Successful research and development require solid know-how about the AI technologies and its possibilities combined with domain knowledge of nuclear energy and nuclear safety. On the other hand, combining knowledge and know-how in new technologies with a dedicated application domain requires sharing the knowledge and know-how – in practice, communication and collaboration.

The elements for successful research and development of AI applications in general are in good or even excellent shape in Finland. The prerequisites and resources for research are good, there are mature technologies and their implementations available even for free as open source tools and solutions. The computing resources and infrastructures are in good condition, including common computing technologies, and computing facilities and services. Availability of relevant and valid data has been earlier identified as an issue, but that is improving as organisations are beginning to understand the value of data and are collecting and, to some extent, sharing it. The competence resources are already in fairly good level and new experts are graduating in fast pace from the universities. Commercial services are available for technology and solution development as well as for AI related services, including competence training. All this means that the starting point for new areas of research in AI applications is good, but the expectations and investments are big, and the competition of the availability of talented experts and the overall competition in research and industry are tough.

The main findings and the recommendations for large AI related research themes in nuclear energy domain are summarised in the Executive summary on page 4 and the research themes are discussed in more detail in Section 5.1. The collected and categorised research themes are summarised in Appendix A and the research theme proposals, based on the collected themes, are summarised in Appendix B. The proposed themes include topics that build common basis for further, efficient research and development within the domain, such as common vocabularies, as well as general new topics, such as knowledge extraction and knowledge engineering, metadata and the organisation of data and information, and data analytics and data visualisation. Another large theme focuses on the main processes in the domain, such as concrete authority processes and systems engineering processes. The third theme group is AI in operator environment, e.g. in condition monitoring, fault and anomaly detection, and in the intelligent support of the operator. The fourth theme group collects other topics and application areas of AI within the nuclear domain. As research in general, when done properly, contains the unpredictable learning and innovation element, the fifth theme in research, the yet unknown applications, should be left open for future proposals. The field of AI is progressing very fast, and new technologies and new ideas for applications are appearing almost in daily basis, and there can be new very valuable topics coming up also for the nuclear safety domain. Constantly following the research and keeping our minds open for new points of view and new ideas, and having agile research and development instruments guarantee the best prerequisites for successful research and innovation.

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Appendix A: Research theme categories

Main research theme category	Description of the theme category
Condition monitoring, anomaly and fault detection, system behaviour prediction	- Use of AI in system monitoring, fault and anomaly detection, analysis of sensor and monitoring data, applications of data analytics. - The relation of the topic to the nuclear authority processes is that the approach in general, and the methods and their implementations need to be studied and developed further, validated and made commonly available so that they are accepted by the nuclear authority and the other stakeholders.
Data analysis, complexity management, data visualisation, dependency analysis, information management, natural language processing, operational processes	- AI in data analytics and data complexity management, dependency analysis and dependency management, visual data analytics. Applications from engineering design process to authority services, artefact and activity management and follow-up. - Automating information management in authority process by using dependency analysis, natural language processing, and knowledge engineering technologies. Automatic generation of metadata.
Data management, data analysis, information management, operational processes	- AI method development and general application of AI methods in nuclear energy sector for data management and for efficient use of data.
Data security, cyber security, data analysis	- Security related topics, taking into account both plant and organisation internal aspects as well as threads coming from outside. - Application of data-based methods and approaches in practise, security of computations and using computing resources, secure and optimal use of existing resources, such as cloud computing, external data lakes and data vaults.
Data strategy, definition work	- General data strategy research and development, meaning and value of a data strategy, specific features of the nuclear domain on the management and use of data within an organisation and a network of organisations. - Elements of the domain common data strategy.
Material engineering, data modelling	- Application of AI in material engineering, in theoretical, experimental and computational research. Method and theory development, practical applications. - The relation of the topic to the nuclear authority processes is that the approach in general, and the methods and their implementations need to be studied and developed further, validated and made commonly available so that they are accepted by the nuclear authority and the other stakeholders.
Natural language processing, data analysis	- Information and its representation transformations, automation of information and knowledge management. Information extraction from existing data. - Language independent representation of systems engineering data. Means to extend knowledge, know-how, methods and approaches from the national context to international markets.
Operator support, diagnostics and decision making, expert system and data analysis	- Situational awareness, data analysis and representation, and data visualisation. - Expert and support systems for operators.
Operational process management, data analysis, dependency analysis, process automation	- Complexity management in authority and engineering processes, and automation of process tasks.
Regulation, process automation, process management, systems engineering	- Use of AI in regulation development, complexity management and dependency analysis, data analysis and representation, link with systems engineering. - Link to the regulation work with the application of regulations, data and knowledge representation, automation of operational processes, systems engineering.
Simulation, control systems, surrogate modelling, system behaviour prediction, systems engineering	- Use of AI methods as computational means in engineering, system monitoring, system behaviour prediction and in general systems engineering. - AI, machine learning and e.g. artificial neural networks in computer analysis, as additional elements or to replace e.g. deterministic methods. Hybrid modelling methods and their applications. - The use of AI in real-time or close to real-time applications, such as model-predictive control. - The relation of the topic to the nuclear authority processes is that the approach in general, and the methods and their implementations need to be studied and developed further, validated and made commonly available so that they are accepted by the nuclear authority and the other stakeholders.
Systems engineering, data management, data transformation, model-based systems engineering, requirements, semantics, validation	- AI throughout in systems engineering, in requirements engineering, concept and detailed engineering design, design validation and verification. - Application of model-based systems engineering and applying data intensive methods, development of intelligent engineering design methods and tools - Data, knowledge and information management and exchange in systems engineering. Knowledge engineering, knowledge management and knowledge representation in engineering design, formal methods of managing engineering knowledge, validation and verification based on formal knowledge.
Uncertainty quantification, system reliability	- AI and data analytics in uncertainty quantification and analysis, reliability of data and methods, reliability of physical and computational systems, reliability of engineering design outcomes.
General themes in digitalisation	- General themes of digitalisation in the nuclear energy domain, including topics, such as sensor technology, edge and cloud computing, Industrial Internet of Things (IIoT), data analytics, digital twins and AI.

Appendix B: Summary of research theme proposals

Theme category	Research topic proposal
Knowledge management and knowledge engineering	*Common domain vocabularies, prerequisites for seamless interoperability of systems*: Formal definition of common concepts and terminology in the form of data models, ontologies, knowledge graphs or other general representation. This is the basis for many further research and development topics within the domain.
	Knowledge capture and management: Formal capture and management of knowledge within the processes, management and utilisation of tacit, domain and engineering knowledge.
	Data utilisation and metadata: Processing of lower value data into new information and knowledge. Improved utilisation of existing data and information, e.g. better data search capabilities and data organisation.
	AI in complexity management: Use of graph-based data representation, utilisation of graph analysis, reasoning and inferring of information. Application of data analytics and e.g. machine learning with complex data in complex processes.
AI in engineering design	*Data analytics in engineering*: Application of data analysis and e.g. big data technologies in engineering to extract new information from data. Data-based models of systems and phenomena, application of machine learning.
	Hybrid methods: Combining the data-based approach with other methods, such as deterministic models and simulation. Combining measured or sensor data with e.g. data produced with simulation, application of data analysis and other AI methods.
	Computational big data: Studying systems and phenomena with computational, deterministic and other models, and data analysis. Application of large computational analysis techniques with big data and data analysis approaches.
AI in operation, condition monitoring, and fault and anomaly detection	*Operator support and training*: Use of AI in process operator support and training by applying e.g. advanced data analytics, data visualisation, and expert systems.
	Feature recognition from data: Use of data analysis and machine learning in condition monitoring, and fault and anomaly detection. Recognition of features from data.
	Simulation enriched data: Application of hybrid approach for machine learning in fault and anomaly detection. Representative data generation for e.g. artificial neural network training.
Other research and development themes	*Improvement of administrational and operational processes*: Application of AI technologies in various places of administrational and operational processes, taking the human aspects into account.
	Media and social media follow-up: Application of natural language processing, data analytics and machine learning on media and social media data to recognise patterns and features.
	Overall security and cyber security: Use of AI in security and cyber security analysis, engineering and monitoring.