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Research article

Human factors engineering simulated analysis in administrative, operational and maintenance loops of nuclear reactor control unit using artificial intelligence and machine learning techniques

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ABSTRACT

The nuclear reactor control unit employs human factor engineering to ensure efficient operations and prevent any catastrophic incidents. This sector is of utmost importance for public safety. This study focuses on simulated analysis of specific areas of nuclear reactor control, specifically administration, operation, and maintenance, using artificial intelligence software. The investigation yields effective artificial intelligence algorithms that capture the essential and non-essential components of numerous parameters to be monitored in nuclear reactor control. The investigation further examines the interdependencies between various parameters and validates the statistical outputs of the model through attribution analysis. Furthermore, a Multivariant ANOVA analysis is conducted to identify the interactive plots and mean plots of crucial parameters interactions. The artificial intelligence algorithms demonstrate the correlation between the number of vacant staff jobs and both the frequency of license event reports each year and the ratio of contract employees to regular employees in the administrative domain. An AI method uncovers the relationships between the operator failing rate (OFR), operator processed errors (OEE), and operations at limited time frames (OLC). The AI algorithm reveals the interdependence between equipment in the out of service (EOS), progressive maintenance schedule (PRMR), and preventive maintenance schedules (PMRC). Effective machine learning neural network models are derived from generative adversarial network (GAN) algorithms and proposed for administrative, operational and maintenance loops of nuclear reactor control unit.

1. Introduction

The field of human factor engineering encompasses a wide range of activities, including the reduction of human errors in the workplace, the enhancement of a company's productivity through the management of human interaction with relevant processes, the guarantee of the safety of both individuals and the working platforms, and the pursuit of the most straightforward means of achieving the objective known as work environment comfort [1–4]. In recent years, there has been a considerable increase in the amount of focus

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Abbreviations

AR	Annunciation of repeated alarming
BMW	Backlog work remaining in maintenance
C	Critical
C/PP	Contractor to plant personal ratio
CRIO	Non operability of machines in control room
EOS	Equipment's existing out of service percentage
HE	Human Error
LER	License Event Report/YEAR
NC	non-critical
NI	Nuclear Industry
NMR	Maintenance requests placed in number
NTP	Number of temporary procedures
OEE	Error occurred during events processed by operator
OFR	Operator fail rate
OLC	Operation at limiting time frame
OTW	Over time worked in functional area
PMRC	The incomplete requests of preventive maintenance
PRMR	Progressive maintenance schedule not achieved
RARM	Error observed in realignment request
RHE	Human Errors that are repeated
NRV	Number of repeat violations
SR	The ratio of Supervisory personal
SSR	Reworks in system safety
VP	Vacancy Percentage
WTE	Wrong training errors

placed on the application of human factor engineering to a variety of sectors, particularly environmental control by humanity and medical applications. The application of human factor engineering has been utilized in order to improve the overall standard of living of the human population as a comprehensive whole [5–7]. To be more specific, during the COVID pandemic emergency crisis, human factor engineering played a significant part in improving the effectiveness of different medical processes in order to get better results in a shorter span of time [8–10].

There are many different safety procedure cycles that are employed in the nuclear sector in order to ensure the safety of both the civilian population and the people who are working on the platforms of nuclear reactors. This emphasizes a number of parameters, including human effectiveness in handling emergency situations, the capacities of the human brain, the reduction of errors that occur during operations performed by people, the prevention of errors that occur repeatedly in nuclear protocols, and so on [11–13]. In fact, the countries striving to achieve nuclear power generation plants in recent times are working on the nuclear safety procedurals and creating awareness among the people about the safety procedures related to nuclear plants and radiations [14–16].

Artificial intelligence and machine learning techniques have led to breakthroughs in human-centric appliances, which have improved the quality of life for human society. These advancements have been made possible by the evolution of these approaches corresponding to the artificial intelligence-based ones. This is causing an enormous revolution in the quality of human life, which has a great deal of advantages for those who benefit from it. The welfare of human civilization in every conceivable way is the fundamental objective of these strategies, which are primarily centered on the subject. Additionally, this encompasses the private lives of every individual in addition to their social lives. It is possible to fulfil the requirements of industries with a great deal of attention and to accomplish this in a more extensive manner, reaching new heights that have never been seen before in the course of human history [17–21]. When it comes to achieving sustainability and dependability in a variety of industries, human reliability and human engineering elements play a very important role. This pertains to the areas of design, planning, operational, administrative, and commissioning procedures that are utilized in the manufacturing sector.

The errors that occurred in human factor engineering are responsible for a significant number of the great catastrophes that have occurred throughout history. As a result, numerous iterative models have been built in order to limit the number of human errors that result in severe catastrophes in a variety of businesses that are of public concern. Software that uses artificial intelligence and machine learning is one of the extremely essential techniques that are being used these days to reduce the number of errors that would otherwise be caused by humans. In terms of artificial intelligence algorithms, attribution analysis, and matrix plots, they make a significant contribution by effectively identifying crucial parameters. In addition, the use of machine learning algorithms in conjunction with specialized software's enables the development of efficient monitoring systems for real-time applications [22–25].

The vast majority of accidents that occur at nuclear power plants are attributed to human mistake, which results in permanent harm to both the environment and human society. Consequently, the procedures for damage control are of the utmost importance in the nuclear industries. The mechanisms for damage control, which are primarily based on artificial intelligence and machine learning, have provided the best prospects to regulate nuclear activities with the highest possible reliability and the least amount of harm. In general, surveillance data are collected from sensors that are positioned at important locations on nuclear reactor platforms. These data are then input into artificial intelligence software in order to enable real-time monitoring and damage control systems. In order to develop an effective damage control monitoring and preventive system, this technique incorporates neural network domains, specifically generative adversarial networks systems [26–30].

In order to reduce the likelihood of catastrophic accidents and failures, artificial intelligence and machine learning techniques are being utilized significantly across a wide range of sectors, including nuclear energy facilities. The algorithms employed in artificial intelligence are utilized in the process of determining the significant variables that influence accidents resulting in unforeseen incidences to take place. Within the nuclear industry, decision support systems, operation validation systems, operation control systems, and autonomous control systems are all now in the process of being developed and implemented by various research groups [31–33].

Based on the results of the literature study, it is evident that there is a significant potential for research on artificial intelligence-based machine learning networks to be employed in nuclear sectors for the purpose of damage control and preventive systems.

2. Design of experimentation

The design of experimentation is categorized to three divisions namely administrative, operational and maintenance levels of nuclear reactor control. As part of simulation and by trial-and-error methods the data of aforementioned categories are set in terms of further classifications of divisions into subdivisions. The successful depiction of AI analysis with these data will enable the same technique which can be utilized in real time applications of damage control mechanisms of nuclear power reactors. Moreover, it is important to realize that the subdivisional parameters are inter dependent in a division and the analysis will lead to concise output which will predict criticality factors involved. The subdivisional factors considered in administrative loop are as follows; The vacancy in man power at Nuclear Industry (NI) in percentile is represented as VP. The event corresponding to license renewal and reporting in a year is represented as LER. The repeated violations of norms followed in NI is set as NRV. HE represents the human error accumulated in a year and RHE represents the repeated human errors which is assumed to be critical in damage control. The overtime works planned and executed in functional areas of NI is termed as OTW.

The ratio of contractual personals to the regular working personals of NI is termed as C/PP whereas the supervisory ratio of all the plants of NI is represented as SR. Criticality of the parameters is set as “C” and non-criticality of parameters is set as “NC”. In the operational loop, the failing rate of operator in various processes of evaluation is termed as OFR. Some operations required to be executed in limiting time frames and denoted as OLC. OEE represents the error occurred during the events carried out by the operator. Operability of machines in the control room is termed as CRIC. ARC represents the annunciation of repeated alarming in NI. Temporarily designated procedures in numbers is termed as NTP. The maintenance loop involves parameters namely EOS representing the equipment’s of out of service condition. SSR represents Reworks requested in system safety. Backlog work remaining in maintenance is termed as BMW. Progressive maintenance schedule achieved in percentage is termed PRMR.

PMRC represents the completed requests of preventive maintenance, Maintenance requests placed in number in NI is termed as NMR. RARM represents the Error observed in realignment request and WTE denotes the wrong training leading to errors [34]. The administrative, operational and maintenance loops are analyzed using WEKA -3 artificial intelligence software to write algorithm concerning the critical and non-critical factors of parameters involved in the specific loops. Multivariant ANOVA treatment are carried out to find out the interactive behavior of the considered parameters to support the artificial intelligence algorithm output. The AI algorithm is derived to draw machine learning algorithm for each loop of NI.

Based on the real-time data that is given by a source that continues to remain private, simulation of the data set is carried out. This simulation is carried out by organizing the parameters that are closely related with catastrophic events in a preferred manner in accordance with the software requirements. The simulation is carried out based on the data set. In addition, the compatibility feature of the program is used to carry out the operation of classifying the various parameters into two primary groups namely critical and non-critical.

The study of artificial intelligence involves importing the dataset into the software, which generates an algorithm that classifies important parameters based on their criticality and non-criticality ranges. This algorithm enables the examination of the

Table 1
Administrative loop analysis in nuclear reactor control.

VP	LER	NRV	HE	RHE	OTW	C/PP	SR	CLASS
0	12	8	40	11	76	0.1	0.96	NC
1	12	11	51	22	230	0.19	0.9	NC
2	13	12	61	21	270	0.23	0.9	NC
3	14	9	47	24	349	0.21	0.89	NC
4	12	11	72	37	378	0.3	0.88	NC
5	12	12	69	28	309	0.32	0.86	C
6	15	10	81	31	365	0.25	0.81	C
7	12	11	93	31	421	0.3	0.79	C
8	13	12	71	29	345	0.25	0.86	C
9	14	14	87	40	398	0.26	0.88	C
10	13	11	91	29	379	0.23	0.87	C

interdependencies among key components. The GAN model, which utilizes unsupervised machine learning, is employed to iteratively create and identify interdependent variables among specified parameters.

3. Results and discussion

3.1. Administrative loop analysis using artificial intelligence and machine learning in nuclear reactor control

A presentation of the simulated data from the administrative loop analysis can be observed in Table 1. The first column of the table displays, in percentage form, is the number of vacant positions in the manpower (VP) department. The table contains a number of parameters that influence the criticality factor, and among those parameters, the critical range is set to be at least five percent of the vacancy of manpower (VP). There is a severe situation in which license event reports (LER) are equal to or more than 15. The number of unfavorable reports must be less than 15 among the many LER that are sent annually. The severity of occurrences of recurrent violence (NRV) is equivalent to or higher than 14, as stated in the preceding section. There is a critical level of human errors (HE) that is observed to be equal to or higher than 81.

It randomly happens that one of the crucial characteristics that determines the criticality of a damage control unit is the number of repeated human mistakes, often known as RHE. In the instance of RHE, the range of criticality is defined as being at least 40. Over time working (OTW) is something that happens to be equivalent to 379 or more, which is portrayed as the critical range.

On the other hand, the ratio of 0.32 or higher is considered to be the criticality in the case of the ratio of contractual personals to plant personals in quantity. In situations where the supervisory ratio (SR) is lower than 0.88, it is considered to be critical.

Presented in Fig. 1 is the algorithm for artificial intelligence, which consists of five levels of administrative loops [35–37]. The

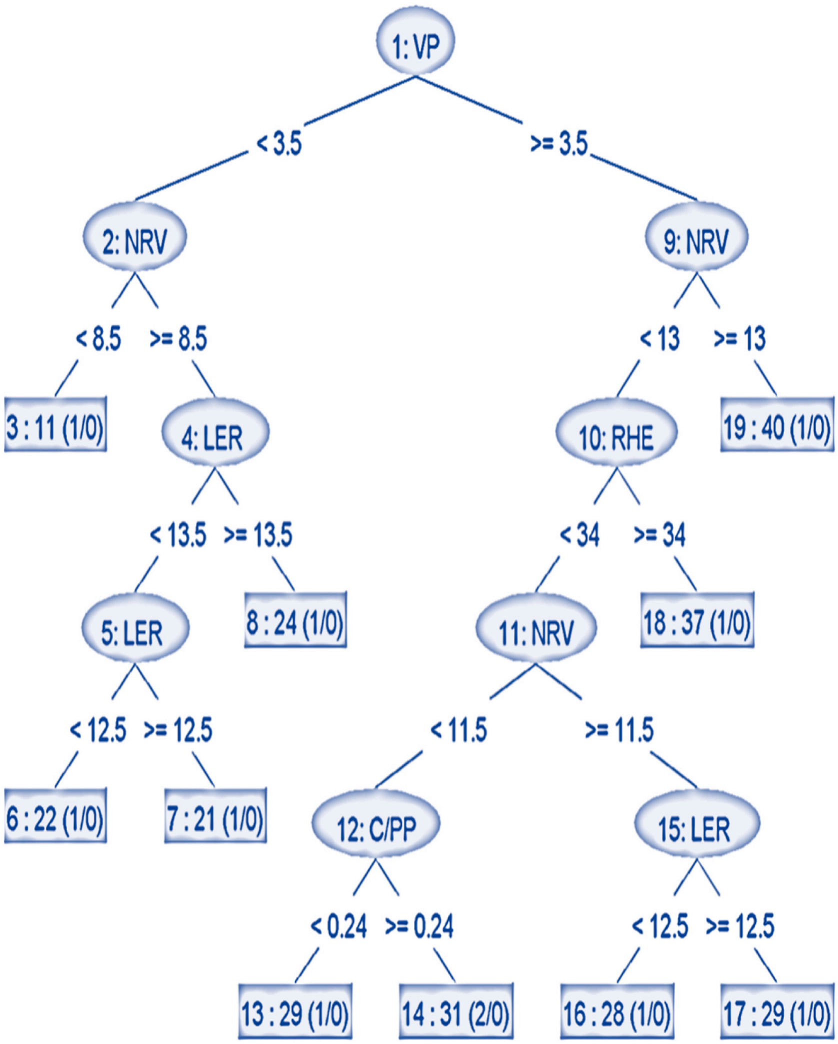

Fig. 1. Artificial intelligence algorithm of administrative loop analysis.

target criteria is considered to be the percentage of vacant positions in the workforce. Due to the fact that all three of the domains that are being studied in this paper namely, administration, operation, and maintenance depend on having sufficient man power, the vacancy in man power could result in various severe errors. In accordance with the method for artificial intelligence, the subsequent layer is comprised of violations that have occurred multiple times.

It is separated into two leafing systems, with a severity level of 1 and a range of 13 and above being classified as classified as critical. LER and RHE make up the subsequent layer, which we will go through as we progress through the layers. When it comes to LER, the criticality is classified as being equal to or greater than 13.5, and the severity level is set at 1. This is in conjunction with NRV. The RHE is considered to be critical with a severity level of 1 when it is equal to or more than 34. NRV and LER are the ones who own Layer 4. The LER is found to be at severity level 1 in conjunction with NRV, as seen by the fourth layer. In addition to this, In the fifth layer, a C/PP ratio that is equal to or greater than 0.24 is considered to be of severity level 2 in conjunction with NRV.

C/PP, LER, NRV, and RHE are the key characteristics that have been discovered as having an impact on the criticality levels of damage control units in the nuclear sector. This is the case when the VP is targeted as the parameter of interest. When VP is considered to be the target parameter in the case of an artificial intelligence system for administrative loop analysis, HE, OTW, and SR are the parameters that are deemed to be secondary. The algorithm predicts the contractual persons to plant working personal ratio is to be at severity level two revealing that the C/PP factor to be monitored critically when associated with other mentioned parameters.

The attribution analysis of the many components that contribute to the functioning of the administrative loop is depicted in Fig. 2. It is common knowledge that the attribution graph illustrates each and every parameter by breaking it down into two leaves. The other one corresponds to class 2, which is known as the critical range represented in red, whereas the first one corresponds to class 1, which is known as the non-critical range represented in blue. The criticality happens to be observed clearly in two ways from the attribution graphs. Firstly, the overlapping of the critical factor leaf with the non-critical factor leaf, which demonstrates that the severity of the parameter can be found in a variety of degrees. Secondly, the extent to which the leaf lengths of critical and non-critical regions differ from one another, along with an indication of which of the two is more dominant [38–40]. In Fig. 2, it is noted that the critical leaf of the VP, LER, and NRV overlaps with the non-critical leaf, indicating that these parameters are significant variables in determining the operation of the damage control unit. On top of that, the differential in leaf strength as well as critical leaf dominance constitutes a phenomenon that is present for c/pp. The attribution analysis of the artificial intelligence test run identifies the critical parameters as vacancy in man power, License event report, repeated violations of norms, and the ratio of contractual personals to the regular plant workers, among the many parameters that are considered. As a result, it is possible to state that this analysis identifies the critical parameters to be evaluated.

The naïve bayes classifier analysis shown in Table 2 consists of following parameters; The F-measure is calculated as the harmonic mean of a technique's accuracy as well as recall values. The Matthew's correlation coefficient (MCC) quantifies the disparity between observed and true values. The true positive rate is The True Positive Rate is a measure that represents the proportion of accurate forecasts in the predictions of the positive class.

The FP rate, or False Positive Rate, is a measure of the risk that a false alert may occur. The ROC area is a metric that quantifies the overall performance of a binary classifier by analyzing the receiver operating characteristic. The PRC region refers to the plot that displays the precision values for associated sensitivity (recall) values in a precision-recall (PRC) plot. TP rate, precision, recall, F-Measure and PRC area values are nearing 1. Henc it can be concluded that the artificial intelligence test run is valid [38–40].

A representation of the interaction plot for the recurring human error component is depicted in Fig. 3. RHE is considered to be a target parameter owing to the fact that it is one of the most important aspects in determining the functioning of the damage control unit. The interaction plots are created through the use of a multivariate analysis of variance test.

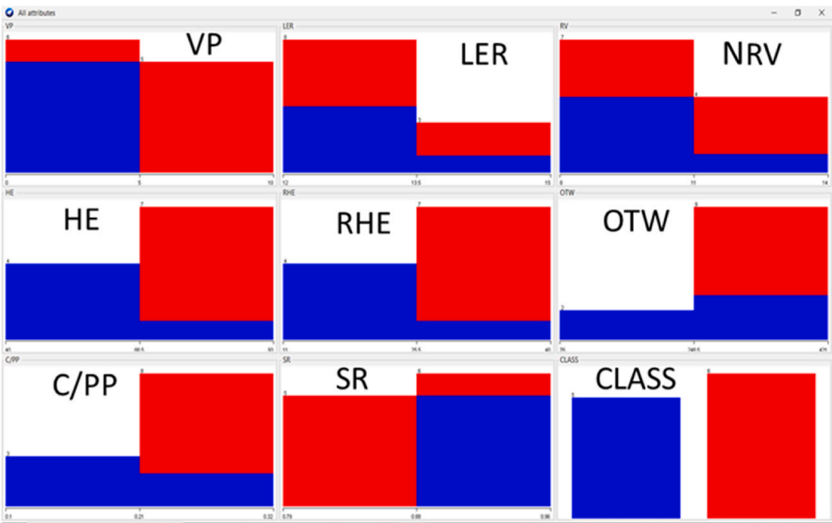

Fig. 2. Attribution analysis in administrative loop.

Table 2
Naïve Bayes classifier results of artificial intelligence out put.

TP RATE	FP RATE	PRECISION	RECALL	F-MEASURE	MCC	ROC AREA	PRC AREA	CLASS
0.800	0.167	0.800	0.800	0.800	0.633	0.817	0.731	NC
0.833	0.200	0.833	0.833	0.833	0.633	0.817	0.785	C
0.818	0.185	0.818	0.818	0.818	0.633	0.817	0.761	WEIGHTED AVERAGE

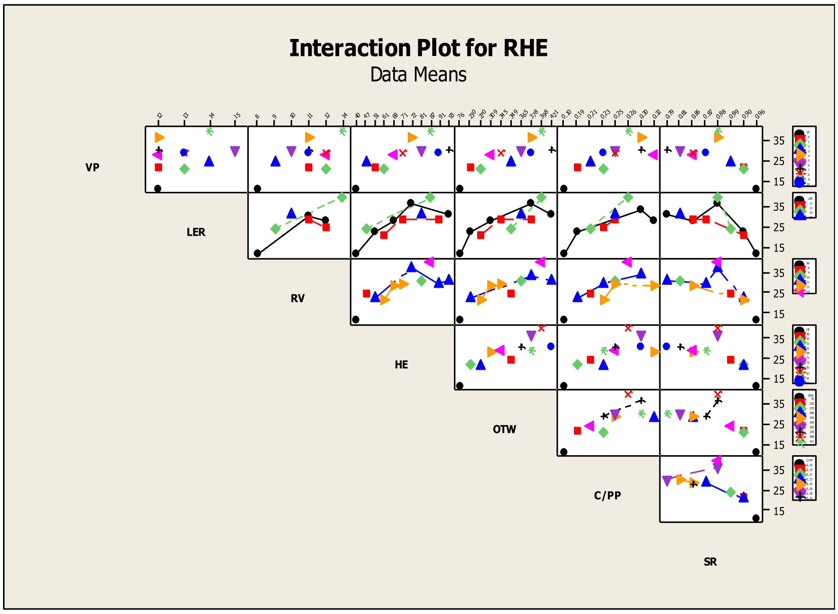

Fig. 3. Multi variant ANOVA analysis result with interaction plots of RHE parameter.

The initial observation makes it quite evident that the plot does, in fact, demonstrate clear interactions with all of the parameters throughout the whole plot. On the other hand, a greater degree of interactions is seen when LER is combined with RHE variables. Similarly, the NRV and C/PP parameters are the ones that are experiencing the next level of interaction, which is the next degree of

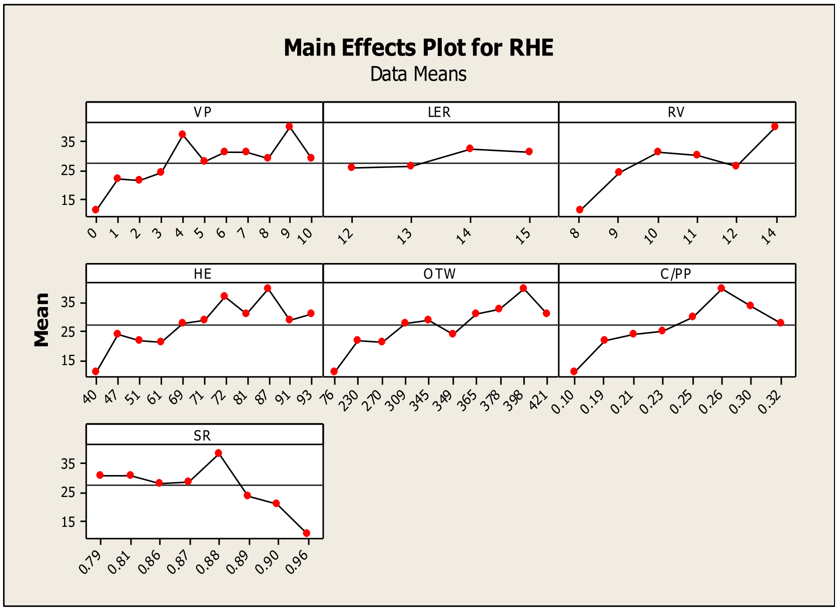

Fig. 4. The main effect plot of RHE with other parameters in multivariant ANOVA treatment.

interaction. Consequently, this demonstrates that the RHE factor is severely affected by the influence of the LER, NRV, and C/PP factors. This result provides strong support for the findings that were obtained from the outputs of the artificial intelligence program. The main effect plots of the means of the various parameters that were taken into consideration during the ANOVA treatment test run are displayed in Fig. 4. By illuminating the narrow mean existence that is connected with LER, VP, NRV, and C/PP, this result also lends support to the outcomes of the artificial intelligence [41–43].

Fig. 5 illustrates the neural network model of the administrative loop that serves as an example of machine learning iteration. There is an input layer, hidden layers, and an out layer that make up this structure. Primary and secondary layers are the components that make up the concealed layer. The primary layers are established according to the critical parameters that determine the proper functioning of the damage control unit nuclear reactor, whilst the secondary layer is comprised of the secondary parameters that are used in the administrative loop. In the image caption of Fig. 5, the iterative conditions are presented [44–46].

3.2. Operative loop analysis using artificial intelligence and machine learning in nuclear reactor control

The parameters that are involved in the functioning of the operating loop are displayed in the simulated Table 3. The operator failing rate, often known as OFR, is one of the essential indicators that must be regularly monitored by continuous monitoring. For a limited amount of time, also known as OLC, certain operations are required to be performed. The error that occurred during the events that took place in the nuclear reactor control operating schedules is represented by their OEE. The ability of machines in the control room not to function properly is referred to as CRIO, and it is an additional aspect that plays a significant role in the operation of the damage control unit.

The abbreviation ARC is often understood to be an announcement of repeated alarming in nuclear reactor control. NTP is an abbreviation that refers to operational methods that are only temporary in nature. The method for operational loop analysis is depicted in Fig. 6, which is an example of artificial intelligence. The non-operability of machines in the control room (CRIO) is the crucial parameter that the algorithm selects as its target. It is classified as "YES," which indicates that there are some machines that are not in working condition, and "NO," which indicates that there is not a single machine that is experiencing issues in its operation.

Due to the fact that it is the comprehensive representation of errors that are being registered in the operative loop, the algorithm clearly guides the parameter in conjunction with CRIO in succeeding layer as error occurred during events (OEE). It has been determined that the critical level of OEE should be equal to 11 or above, with a severity level of 1. Because of this, the third layer of the algorithm was able to incorporate OEE, OLC, and OFR into its structure. When it comes to the operation within the restricting time frame, the criticality level is equal to or higher than 25, and the severity level is 1. A criticality level of 3.5 or higher is associated with the operator failure rate (OFR), while a severity level of 1 is associated with the operator efficiency (OEE). The algorithm determines that the criticality level for the temporary procedures in numbers (NTP) is 35.5, and that the severity level for the whole range of NTP is 1. Consequently, the OEE, OLC, and NTP have been identified as the key crucial parameters in the operative analysis loop of the nuclear reactor control unit respectively.

A representation of the attribution analysis of the operative loop in nuclear reactor control is shown in Fig. 7. Specifically, OFR OLC and OEE are the measures that demonstrate the overlaps that exist between primary and secondary leaf levels. In the instance of OEE and OFR, there is a discernible overlap that can be seen, which reveals the impact that criticality has on both leaves together. Furthermore, it has been noted that the difference in leaf lengths is the greatest in the case of NTP, which demonstrates the significance of the parameter. As can be seen in Table 4, the values for TP rate, precision, recall, F-measure, and PRC area are becoming closer and closer to 1. Because of this, it is possible to draw the conclusion that the test run of artificial intelligence is reliable [38–40].

Fig. 8 shows an interaction plot representation for operator failing rate (OFR) component. Since OFR is one of the most crucial factors in determining how well the damage control unit operates, it is regarded as a target parameter. A multivariate analysis of

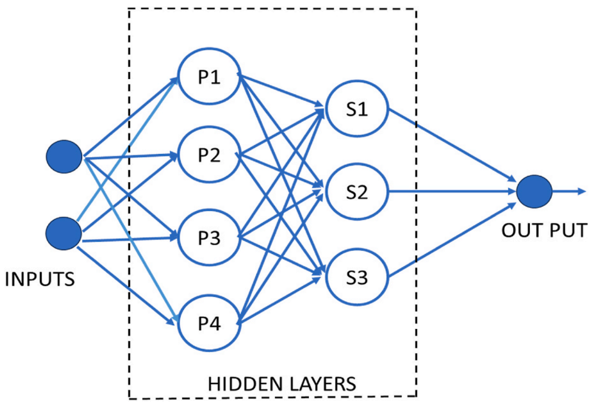

Fig. 5. Suggested neural network model for machine learning iteration of administrative loop ((P_1=C/PP; Critical ≥0.24, Max = 0.32), (P_2 = LER; Critical ≥12.5, Max = 15), (P_3=NRV; Critical ≥11.5, Max = 14), (P_4 = RHE; Critical ≥34, Max = 40), (S_1=HE, Max = 93), (S_2 = OTW, Max = 421), (S_3=SR, Min = 0.88), (S_4=VP, Max = 10)).

Table 3
Operational loop analysis in reactor control unit.

OFR	OLC	OEE	CRIO	ARC	NTP	CLASS
0	24	7	NO	YES	16	NC
1	24	6	NO	NO	23	NC
2	26	8	NO	NO	26	NC
3	28	9	NO	NO	31	NC
4	24	11	NO	NO	33	NC
5	24	9	NO	NO	38	C
6	30	10	YES	YES	39	C
7	24	14	YES	NO	42	C
8	26	13	YES	YES	39	C
9	28	14	YES	YES	45	C
10	26	12	YES	YES	22	C

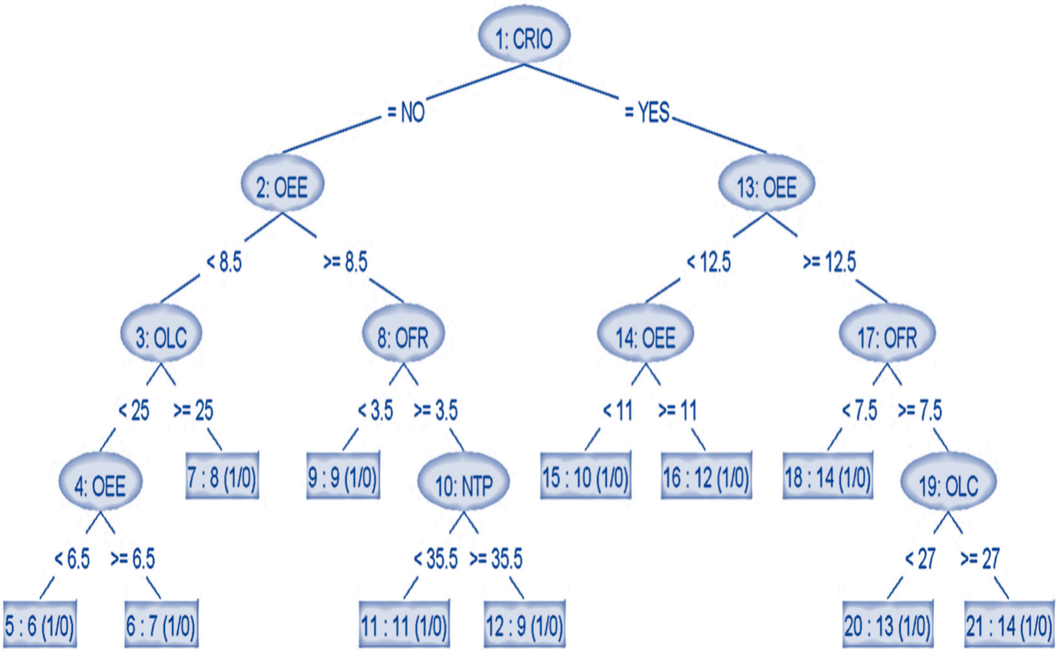

Fig. 6. The artificial intelligence algorithm of operational loop analysis.

variance test is used to construct the interaction graphs. The first observation clearly indicates that the plot exhibits distinct interactions with all of the factors throughout its entirety. Conversely, there is a higher level of interactions observed when OFR is paired with OLC and OEE variables. Hence, the OLC and OEE parameters are undergoing a higher level of interaction, representing the subsequent degree of interaction vice versa.

Therefore, this indicates that the OFR factor is significantly impacted by the influence of the OLC, OEE, and NTP factors. This outcome offers robust validation for the conclusions derived from the artificial intelligence program's outputs. Fig. 9 displays the main effect plots of the means for the different parameters included in the ANOVA treatment test run. This graph provides more evidence for the findings of artificial intelligence [41–43] by showing the interacting nature of OLC, OEE and NTP.

The neural network model of the operative loop, which provides an example of machine learning iteration, is shown in Fig. 10. This structure consists of an input layer, hidden layers, and an out layer. The concealed layer is composed of two layers: primary and secondary. The secondary layer is made up of the secondary parameters that are utilized in the administrative loop, whereas the primary layers are set up in accordance with the critical parameters that dictate how well the damage control unit nuclear reactor operates. The iterative conditions of the operative loop analysis are presented in the image caption of Fig. 10 [44–46].

3.3. Maintenance loop analysis using artificial intelligence and machine learning in nuclear reactor control

Maintenance loop analysis consists of various parameters to be analyzed in AI test run for identifying primary critical parameters. EOS represents the equipment's existing in out of service condition. SSR represents the reworks in system safety, BMW denotes backlog work remaining in maintenance and progressive maintenance schedule not achieved in percentage is termed as PRMR. The incomplete

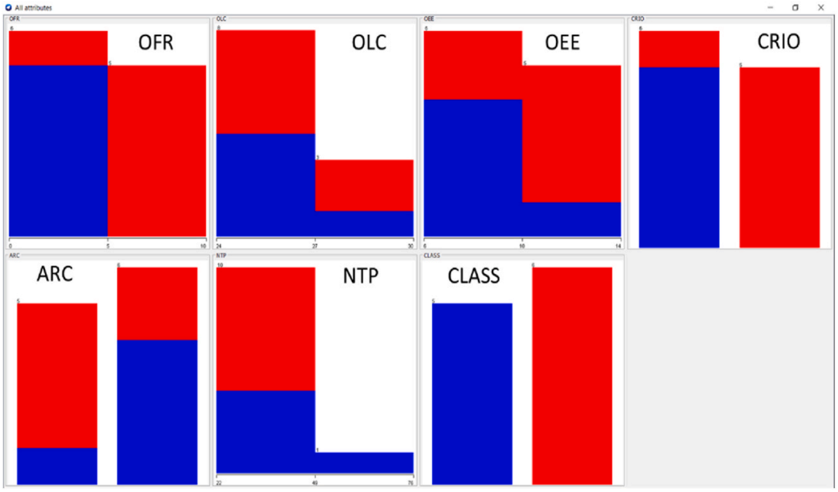

Fig. 7. Attribution analysis in operative loop.

Table 4
Naïve Bayes classifier results of artificial intelligence out put.

TP RATE	FP RATE	PRECISION	RECALL	F-MEASURE	MCC	ROC AREA	PRC AREA	CLASS
0.800	0.167	0.800	0.800	0.800	0.633	0.817	0.731	NC
0.833	0.200	0.833	0.833	0.833	0.633	0.817	0.785	C
0.818	0.185	0.818	0.818	0.818	0.633	0.817	0.761	WEIGHTED AVERAGE

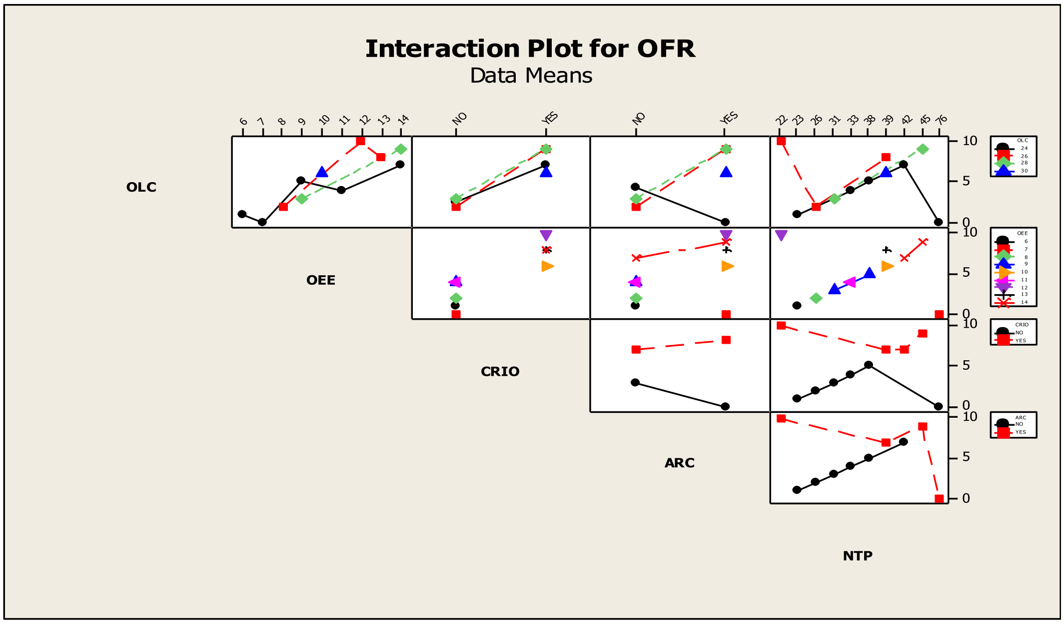

Fig. 8. Multi variant ANOVA analysis result with interaction plots of OFR parameter.

requests of preventive maintenance are represented as PMRC while maintenance requests placed in number is depicted as NMR. RARM represents error observed in realignment request and WTE refers to the wrong training leading to errors. The development of the simulated table is carried out with a great deal of concentration since maintenance is an essential activity that must be accomplished to guarantee that the nuclear reactor will continue to operate continuously. Table 5 represents the maintenance loop analysis with all the parameters considered.

The algorithm for maintenance loop analysis is depicted in Fig. 11, which is produced using artificial intelligence. Due to the fact

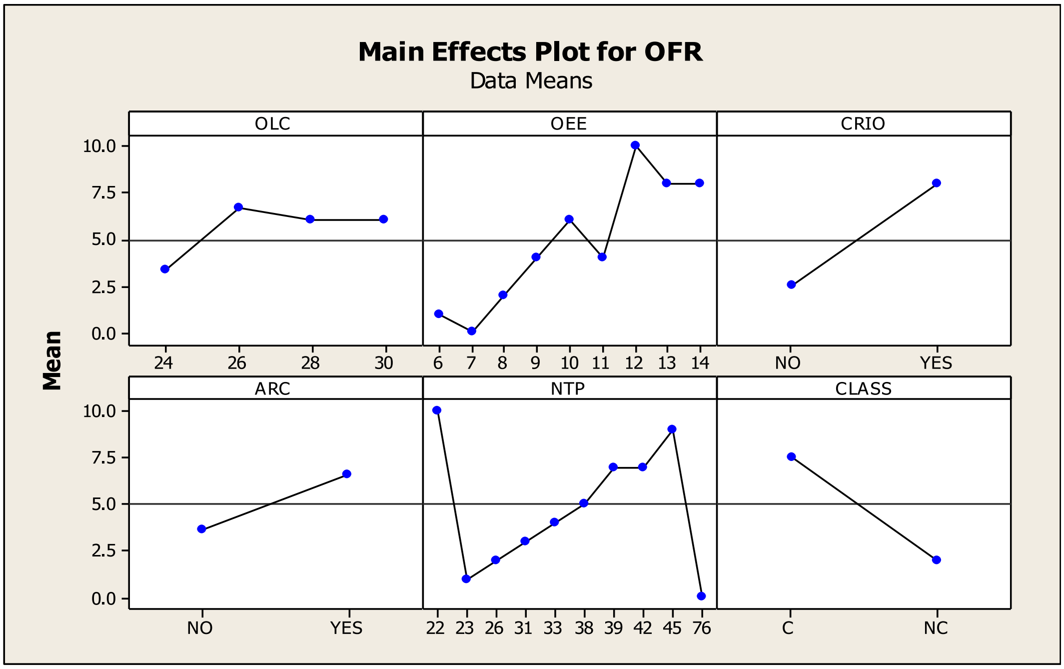

Fig. 9. The main effect plot of OFR with other parameters in multivariant ANOVA treatment.

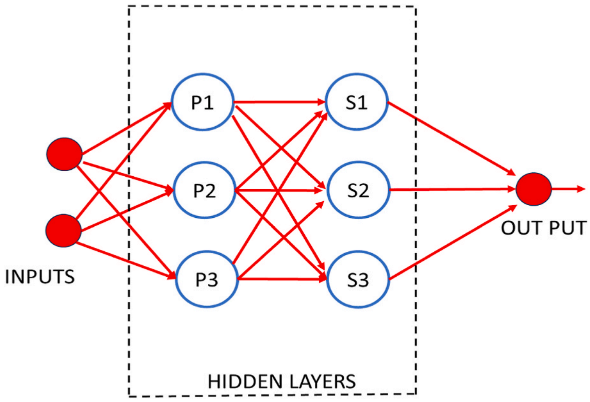

Fig. 10. Suggested neural network model for machine learning iteration of operative loop ((P_1= OEE; Critical ≥11, Max = 14), (P_2 = OLC; Critical ≥25, Max = 30), (P_3 = NTP; Critical ≥35.5, Max = 45), (S_1=CRIO), (S_2 = ARC), (S_3=OFR)).

Table 5
Maintenance loop analysis in reactor control unit.

EOS	SSR	BMW	PRMR	PMRC	NMR	RARM	WTE	CLASS
0	26	6	30	18	123	2	23	NC
1	28	8	27	22	89	4	19	NC
2	39	12	41	24	134	6	11	NC
3	36	10	38	30	145	5	23	NC
4	45	11	60	37	139	8	29	C
5	48	12	69	32	141	12	31	C
6	49	15	71	29	124	11	34	C
7	39	11	34	31	198	15	54	C
8	51	17	64	42	203	17	23	C
9	50	20	56	40	243	13	45	C
10	56	21	91	47	231	16	39	C

that the concerned result will lead to catastrophes if it continues to progress to accident level, the goal parameter has been selected as the request for preventive maintenance that has not been performed (PMRC). The artificial intelligence algorithm is built with the presence of five layers along with a variety of leaf types.

The subsequent layer involves the combination of PRMR and EOS using PMRC as the base. Because there is a lack of human effort to repair the necessary machines, the fact that the equipment is currently in a state of being out of service (EOS) is the principal cause for concern. Furthermore, the PMRC is directly dependent on the progressive maintenance plan (PRMR) that is approaching its due date. It just so happens that the critical level of PRMR is in the range of 32 and higher. The criticality of the second layer is determined by the proportion of all equipment that is currently out of service (also known as EOS). Due to the fact that the EOS parameter is a crucial role in the functioning of the damage control unit, it is present in four successive layers of the algorithm. It is for this reason that the combination of EOS with a number of parameters, specifically PMRC, PRMR, and RARM, takes up the majority of the algorithm's leaves. From this, it can be deduced that the EOS in the maintenance loop is the most important essential parameter.

When the severity level of EOS is equal to or more than 1, the critical level of EOS is established. An additional essential component that is being incorporated into the second layer of the algorithm is the error that is recognized in the realignment work (RARM). Furthermore, the third layer incorporates the parameter commonly referred to as WTE, which stands for the incorrect training that results in an error with a criticality factor equal to 21 or higher and a severity level of 1. It just so happens that the critical level of RARM is comparable to 11.5 and above. As a result, the algorithm demonstrates that the PMRC, EOS, WTO, and RARM parameters are the most important crucial factors in the maintenance loop.

In Fig. 12, the attribution analysis of the maintenance loop is presented. In the case of EOS, PRMR, PMRC, and WTE, the analysis makes it abundantly evident that there is a presence of overlapping between the primary and secondary leaf structures.

It can be deduced from this that the EOS, PRMR, PMRC, and WTE parameters are the key factors that contribute to the performance of the damage control system. As is evident from the data presented in Table 6, the values for TP rate, precision, recall, F-measure, and PRC area are increasing until they are precisely equal to 1. As a result of this, it is feasible to arrive at the conclusion that the test run of artificial intelligence is both reliable and legitimate [38–41].

A representation of the interaction plots for the equipment out of service (EOS) parameter may be found in Fig. 13. The charts demonstrate that there is a comprehensive interaction between the parameter that was chosen and the other aforementioned parameters. The parameters WTE, PMRC, PRMR, and RARM all exhibit a discernible interaction with one another. The findings of the artificial intelligence treatment outputs in terms of the algorithm and the attribution chart are showing that this is almost supporting the results. The plots of the mean vs the main effect that are shown in Fig. 14 show that the points that are closest to the mean are found in the cases of PRMR, PMRC, RARM, and WTE. This is in accordance with what was expected by the interaction plot about the mean [41–43].

Fig. 15 depicts the neural network model of the maintenance loop, which serves as an illustration of an iteration that can be performed by machine learning. An input layer, hidden layers, and an out layer are the components that make up this overall structure.

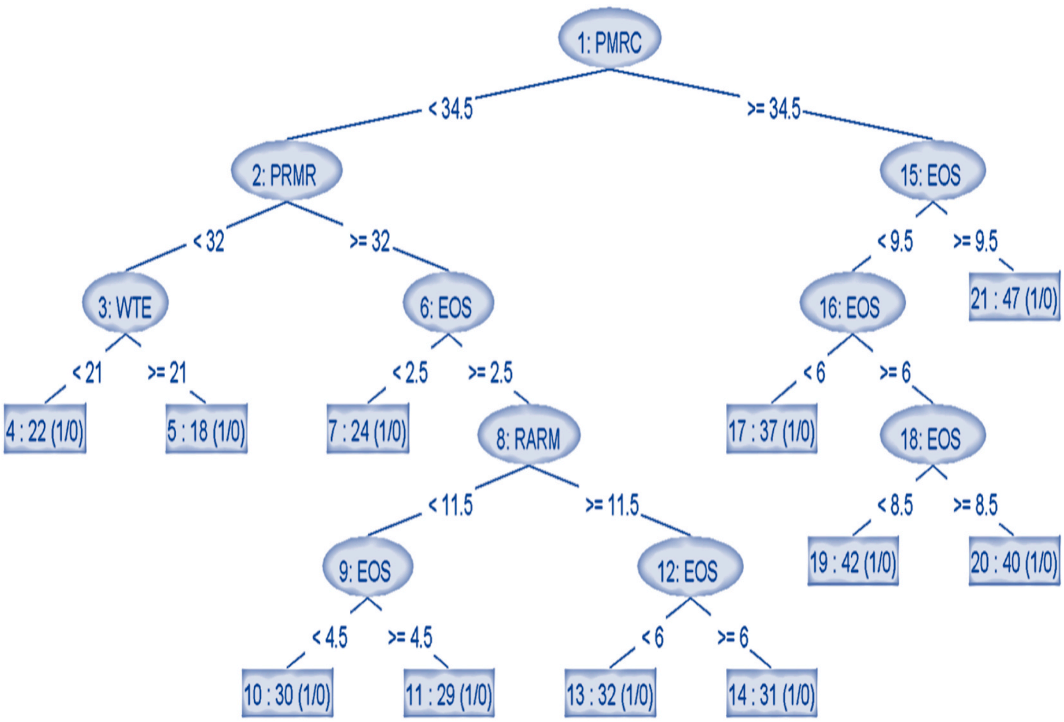

Fig. 11. Artificial Intelligence Algorithm of maintenance loop analysis.

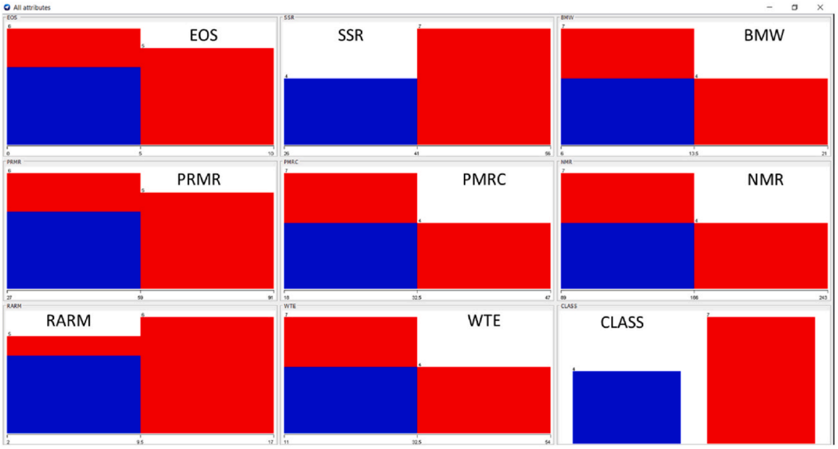

Fig. 12. Attribution analysis in maintenance loop.

Table 6
Naïve Bayes classifier results of artificial intelligence out put.

TP RATE	FP RATE	PRECISION	RECALL	F-MEASURE	MCC	ROC AREA	PRC AREA	CLASS
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	NC
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	C
1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	WEIGHTED AVERAGE

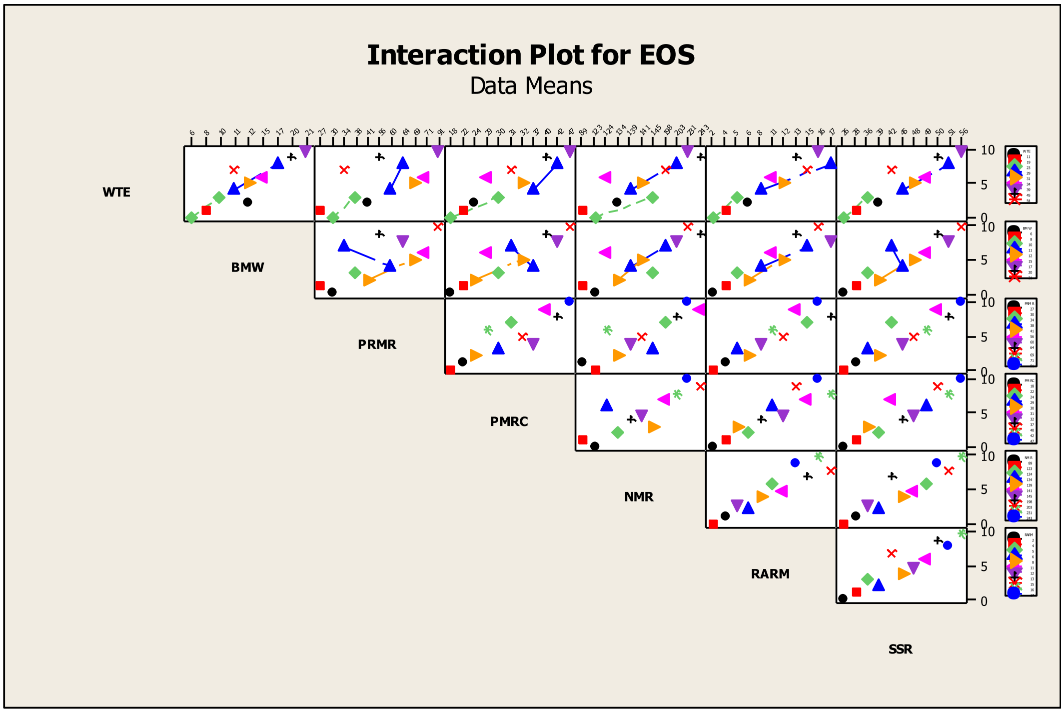

Fig. 13. Multi variant ANOVA analysis result with interaction plots of EOS parameter.

There are two layers that make up the concealed layer: the primary layer and the secondary layer. In contrast to the primary layers, which are organized in line with the important parameters that determine how efficiently the nuclear reactor damage control unit functions, the secondary layer is composed of the secondary parameters that are utilized in the administrative loop. Image caption of Fig. 15 [44–46] presents the iterative conditions of the operating loop analysis.

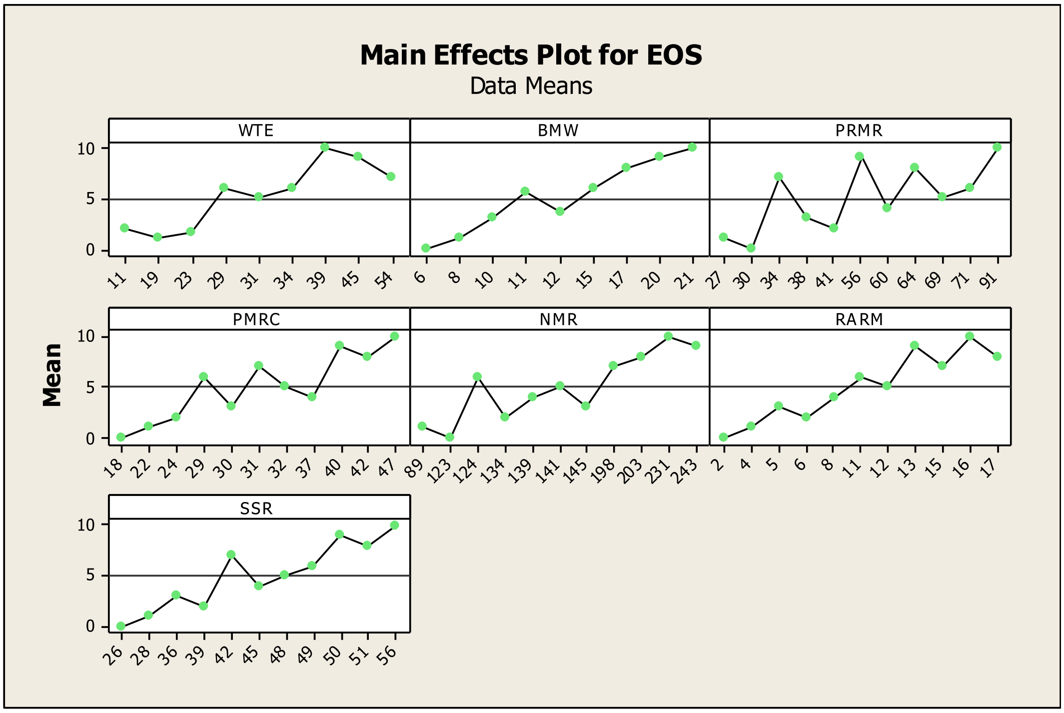

Fig. 14. The main effect plot of OFR with other parameters in multivariant ANOVA treatment.

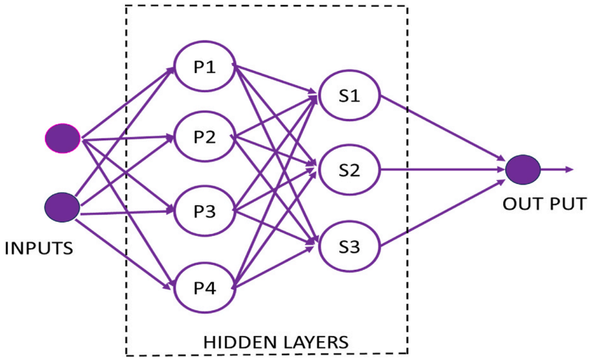

Fig. 15. Suggested neural network model for machine learning iteration of maintenance loop ((P_1 = EOS; Critical ≥4, Max = 10), (P_2 = PRMR; Critical ≥56, Max = 91), (P_3 = PMRC; Critical ≥31, Max = 47), (P_4 = WTE, Critical ≥29, Max = 54) (S_1= BMW, Max = 21), (S_2 = NMR, Max = 243), (S_3==SSR, Max = 56)).

4. Discussion

It is a well-known fact that the unsupervised machine learning approach has the advantage of being able to recognize a pattern from an unlabeled data set in order to create an iteration with specified parameters and, as a result, to make decisions based on artificial intelligence. The interdependency determinant factor (I) is represented by the formula that is presented below [31].

$$I(D,G) = \mathop{\mathbb{E}}_{r\sim q_r}[log\, D(r)] + \mathop{\mathbb{E}}_{t\sim q_t}[log\,(1 - D(G(t)))]$$

where D represents the discriminative factor revealing the dependency or independent nature of a factor and G represents the generative factor to analyze the selected parameters in a range set during the simulation of the data set. r represents a random pick of data from data set q_r whare as t represents a latent variable selection by the software from the data set q_t.

A representation of the output of unsupervised machine learning with regard to the interdependency factor is shown in Fig. 16.

This output is obtained when an analysis is performed between specified parameters, namely the operator failure rate and the number of temporary operations. The output of the iteration that was formulated in machine learning demonstrates that there is a mathematical conjunction that displaying a clear interdependency variation with regard to one in relation to other.

Fig. 17 illustrates the artificial neural network (GAN) model that was developed using the iForest method for the purpose of computing the interdependency that is closely associated to the anomaly that occurs when comparing two data sets of key parameters of selection. Two of the most influential leaves in the algorithm are the classes known as dependency and independency. These leaves are responsible for the testing, validation, and training of the datasets produced by the algorithm. All of the interdependencies between the important parameters in this study have been effectively recognized using this model [31]. This model has been successfully implemented in the administrative, operation, and maintenance loops of the nuclear reactor control unit, and the outputs that correspond to it enable the damage control units to function in an effective manner. On the basis of these analyses, proposals have been made for effective neural networking models to be implemented in the aforementioned loops of nuclear plant.

The accident conditions are primarily influenced by administrative, operational, and maintenance loops. When it comes to administrative loop, the main elements that directly impact human mistakes and recurrent violations resulting in accident conditions are the recruitment of contractual workers and the number of licensing reports. The accidental situations in the operational loop are directly influenced by fundamental components such as activities occurring within limited time frames, operator error, and temporary procedures. In a maintenance loop, key elements such as the condition of equipment, the schedule for maintenance, preventative measures, and errors in the training schedule are significant determinants that have a profound impact on accident circumstances. Furthermore, the field of artificial intelligence and machine learning has successfully determined the extent of interdependence among the key components that contribute to catastrophic events in nuclear power plants. This result can lead to the implementation of effective safety measures by directing the damage control unit's attention towards critical elements with greater interdependence.

5. Conclusions

The human factor engineering simulated analysis of administrative, operational and maintenance loops functioning of nuclear reactor control unit is performed successfully using artificial intelligence software. The administrative loop analysis resulted in 5-layer AI algorithm and identifies the primary key parameters as ratio of contractual persons to the plant persons (C/PP), License event reports with alarming signals (LER), Number of repeated violations (NRV), and repeated human errors (RHE). The AI algorithm further reinstates that the C/PP ratio has the severity level of 2 with other parameters in conjunction.

The operational loop analysis resulted in 4-layer AI algorithm identifying the Key parameters influencing the nuclear reactor control as error occurred during events performed by the operator (OEE), Operations carried out at limiting time frames (OLC) and temporary procedures in number (NTP). OEE, OLC and NTP have the severity level of 1 in the algorithm.

The maintenance loop analysis resulted in a 5-layer AI algorithm proposing the following parameters as primary influencing ones in damage control unit. They are equipment out of service condition (EOS), Progressive maintenance schedule not achieved (PRMR), Preventive measures requests not achieved (PMRC) and wrong training leading to errors (WTE).

Multivariant ANOVA treatment for the administrative, operational and maintenance loop analysis are run and the corresponding results are in agreement with the results obtained in AI analysis.

A promising neural network model with primary hidden layer consisting key parameters of administrative, operational and maintenance loops are constructed based on the results of GAN model in association with iForest algorithm. A successful GAN model algorithm is introduced to obtain the interdependency correlation among key parameters causing catastrophes in nuclear plant.

Data availability statement

Data will be made available on request.

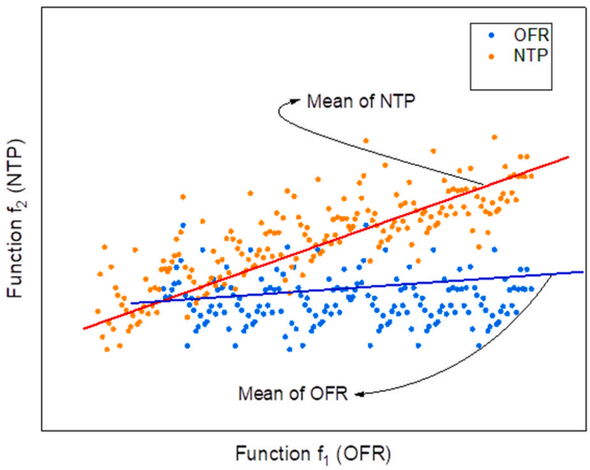

Fig. 16. GAN based unsupervised machine learning output for interdependency between selected parameters OFR and NTP.

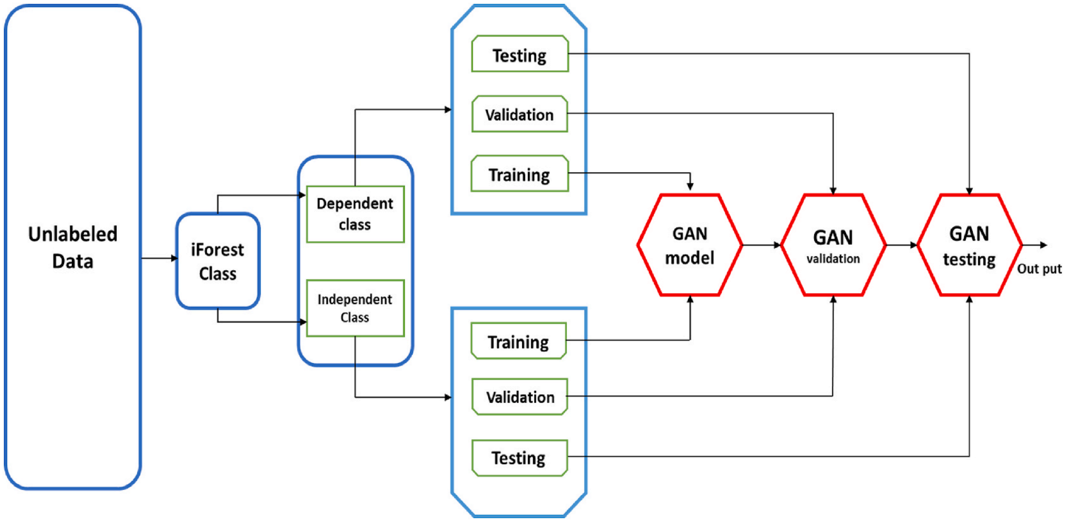

Fig. 17. iForest algorithm-based GAN model for the computation of interdependency of key parameters using machine learning technique.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Abdulrahman Khamaj: Funding acquisition, Formal analysis, Data curation, Conceptualization. **Abdulelah M. Ali:** Supervision, Resources, Project administration, Methodology, Investigation. **Rajasekaran Saminathan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Conceptualization. **Shanmugasundaram M:** Writing – original draft, Visualization, Validation, Supervision, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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