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RISK ANALYSIS OF THE ISU AGN-201M REACTOR AND CONTROL ROD DRIVE CHANGEOVER

by

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The members of the committee appointed to examine the thesis of WESLEY YOCKEY find it satisfactory and recommend that it be accepted.

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RISK ANALYSIS OF THE ISU AGN-201M REACTOR AND CONTROL ROD DRIVE CHANGEOVER

Thesis Abstract

Idaho State University (2022)

The current Aerojet General Nucleonics 201 modified (AGN-201m) reactor at Idaho State University (ISU) has operated for 80 years with the current control rod mechanisms which still allows for adequate SCRAMming of the reactor. The original design involves a double leadscrew which causes binding problems and weight problems with the steel chassis. The proposed new design is lighter-weight and more serviceable than the original design by using newer materials and a single leadscrew design. This thesis provides a risk assessment of the new control rod drive mechanism (CRDM) versus the current CRDM and assists in the required documentation submitted to the Nuclear Regulatory Commission (NRC). The reliability analysis with machine learning yielded a result of 1.980E-10 (mean time to failure (MTTF) 3.15E+07) probability of failure of any two of the current CRDMs and 1.170E-14 (MTTF 5.34E+11) probability of failure of any two of the new CRDMs.

Keywords: Probabilistic Risk Assessment, Aerojet General Nucleonics model 201 modified, AGN-201m, Fussell-Vesely, Rod Drive Mechanism

Chapter 1: Introduction

Idaho State University (ISU) is equipped with a Nuclear Regulatory Commission (NRC) regulated research reactor. ISU acquired the reactor in 1969, and it is still in active operation to this day. The reactor is an Aerojet General Nucleonics 201-Modified (AGN-201m) model; a low power reactor intended for educational and research use applications within the nuclear industry. Globally there are five active AGN-201m reactors, historically there have been a total of 15 AGN-201 reactors in operation.

The control rod drive mechanisms (CRDM) within ISU's AGN-201m are aging components. The current CRDMs are still original and have been functioning well for 80 years. Currently while the rod drives are still guaranteed to allow for adequate ejection from the core, the ability to manipulate the CRDMs in a precise way and without binding of the leadscrews is becoming apparent.

An upgrade to the CRDMs have been proposed in 2017 which aims to be more reliable, lighter weight, and more precise than the current rod drive mechanism [1]. This thesis will demonstrate qualitatively and quantitatively the new rod drive design will operate in a more precise manner and reduce reliability issues of the mechanism controlling the reactivity of the reactor. A grant was proposed and awarded to perform the upgrade in 2020 to allow ISU to undergo upgrading the CRDMs using the design from 2017 [2].

The AGN-20m reactor at ISU does not have a probabilistic reliability assessment (PRA) to model changes made to the reactor. This thesis aims to provide a high-level PRA model of reactor systems in addition to a detailed fault tree model of the CRDM to allow for the potential to model future changes that could be made to the reactor and make statistical predictions.

1.1 Scope of Failure of the AGN-20m Reactor

In the scope of this thesis, failure is defined as the loss of the ability on behalf of the operator to perform reactivity movements. The required SCRAM functionalities are still guaranteed to exist under this definition. The SCRAM functionalities of the current CRDM are still guaranteed to induce a SCRAM under the events described in Table 1. The functions described in Table 1 are **NOT** at risk for the foreseeable future **even if the control rod drive mechanisms are not upgraded.**

Table 1. Reactor Control and Safety Systems Set-Point Specifications [3]

Safety Channel	Set Point	Function
Nuclear Safety Channel No.1 (Startup Count Rate Channel) Low Power	5% full Scale[1] OR 0.5 count/second[2]	Scram at levels Below the set points
Nuclear Safety Channel No.2 (Log Power Channel) High Power	6 watts (120% of licensed power)	Scram at power > 6 watts
Nuclear Safety Channel No.2 (Log Power Channel) Low Power	3.0×10-13 amps	Scram at source levels < 3.0×10-13 amps
Reactor Period	5 sec	Scram at periods < 5 sec
Nuclear Safety Channel No.3 (Linear Power Channel) High Power	6 watts (120% of licensed power)	Scram at power > 6 watts
Nuclear Safety Channel No.3 (Linear Power Channel) Low Power	5% of Full Scale	Scram at levels < 5% of Full Scale
Manual Scram	----	Scram at operator discretion
Area Radiation Monitor	= 10 mR/hr	Alarm at or below level set to meet requirements of 10 CFR 20

[1] Unit A is the original AGN-201m control console.
[2] Unit B is the new ISU all solid-state electronic control console. Either Unit A or Unit B will be in service anytime the reactor is operating.

Chapter 2: Background

2.1 The Aerojet General Nucleonics 201 Reactor

The AGN-201m reactor is a polyethylene moderated uranium fueled reactor power rated for 5 W of thermal power [4]. The reactor is not designed to produce electrical power of any kind. The fuel contains less than a kilogram of fuel enriched to 19.9% uranium-235 [4]. The reactor is comprised of nine fuel disks separated across two halves of the core. The lower half is supported by a polystyrene thermal fuse at the center of the reactor core which is doubly dense in fuel material creating a thermal hotspot [4].

Outside of the reactor core is an aluminum encasement to mitigate gaseous fission product releases. Inside the aluminum encasement around the reactor core are graphite reflectors, lead gamma shields, and outside the aluminum is a water neutron shield to ensure mitigation of radiological concern [4]. The reactor is also covered by concrete and barite bricks to further diminish radiological exposure, and act as a structure for operations personnel to perform surveys on top of the reactor vessel.

Figure 1 shows a cross-sectional view of the different layers within the AGN-201m design including components and general dimensions.

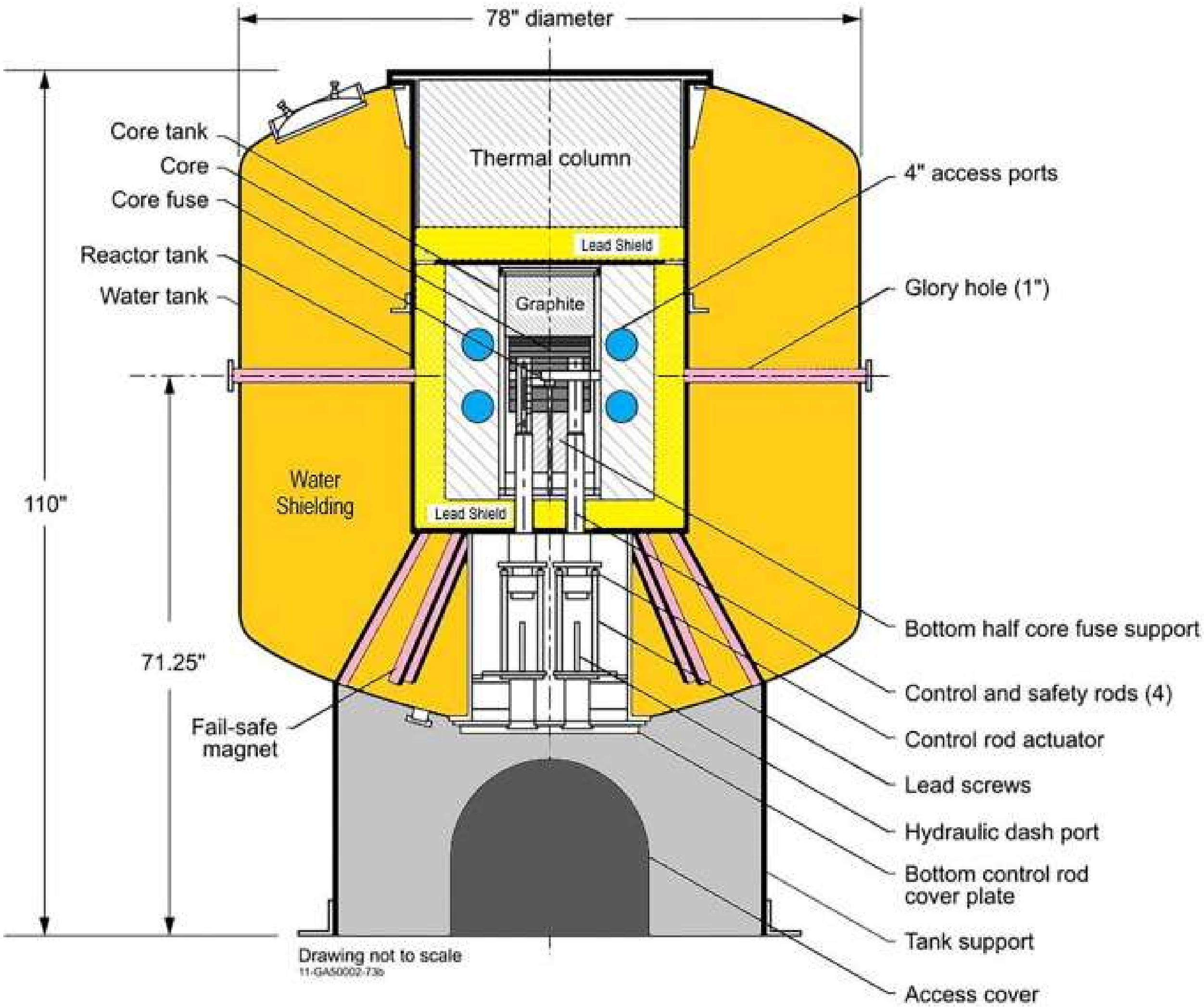

Figure 1. Elevation view of the AGN-201m [5].

The AGN-201m requires various mechanisms of engineering controls, administrative procedures, and organization to maintain an operating license covered by 10 CFR 50. The main mechanical control employed by the AGN-201m reactor is the CRDMs. The AGN-201m has two safety control rod drives and two control rod drives.

2.1.1 Decommissioned AGN-201m reactors

The ISU AGN-201m is one of five currently operational AGN-201 reactors in the world. The four others currently still in operation are University of New Mexico (UNM), Texas Agriculture and Mechanical (Texas A&M), University of Palermo, and Kyung Hee University. Table 2 highlights the operational status of every AGN-201 reactor constructed. There is minimal information as to why many of the AGN-201 reactors were decommissioned. What little information was found on decommissioning implies that most were shut down due to general unrest in the local area, lack of funding, or personnel available to maintain the facility.

Table 2. AGN-201 Reactors Around the World

Name	IAEA Code	Power Rating (W)	Status	Comments
AGN-201 Costanza	IT0010	20.000	Operational	
AGN-201K	KR0003	10.000	Operational	Kyung Hee University, Korea
AGN-201P	CH0002	0.0000	Decommissioned	
AGN-201 California Polytechnic State University	US0144	1.0000	Decommissioned	US Naval Postgraduate School reactor
AGN-201 Catholic University	US0145	1.0000	Decommissioned	
AGN-201 Georgia Institute of Tech	US0096	1.0000	Decommissioned	Former University of Akron
AGN-201 Idaho State University	US0094	5.0000	Operational	Original Prototype from San Ramon
AGN-201 Memphis St. University	US0121	1.0000	Decommissioned	Originally AGN-201 Argonne's
AGN-201 Oregon State University	US0147	0.0010	Decommissioned	
AGN-201 Polytechnic Institute of New York	US0153	0.0010	Decommissioned	Formerly National Navy Medical Center's
AGN-201 Texas A&M University	US0191	0.0050	Operational	

Name	IAEA Code	Power Rating (W)	Status	Comments
AGN-201 Tuskegee Institute	US0146	0.0010	Decommissioned	Formerly Oklahoma State University’s
AGN-201 University Delaware	US0195	0.0050	Decommissioned	
AGN-201 University of New Mexico	US0201	0.0050	Operational	Formerly University of California
AGN-201 University of Utah	US0210	0.0050	Decommissioned	

2.2 Idaho State University AGN-201m Reactor

2.2.1 Changes Made to the Idaho State University AGN-201m

The subject of this project is the ISU AGN-201m reactor. The AGN-201m has undergone a handful of prior changes during its lifetime, forming the foundation of the rod drive changeover project. The changes made to the reactor have extended the operational lifetime well beyond many other AGN-201 models.

The ISU AGN-201m is currently undergoing an amendment to make changes to the reactor’s detector channels. The upgrade plans to replace old boron trifluoride ion chambers with new boron-10 lined ion chambers, maintaining the functionality of the original detectors, improving handling safety, and reducing noise from wear and tear on the equipment.

The ISU AGN-201m console changeover has been the longest upgrade with the most work put into ensuring it happened. The process took many experts and many students 20 years to implement, and there are still improvements being made for quality of life and safety.

2.3 Reactor Rod Drive Designs

The CRDMs are inserted into a confined space below the AGN-201m. The close fit limits the spatial dimensions of any new CRDM design to be similar to the current size and shape of the current CRDM. Figure 2 identifies the differences between the current CRDM (see (a)) and the new CRDM (see (b)) [5]. Prior to discussion of the CRDMs it is important to highlight at a high level the potential failure mode of the equipment included within the two designs. Components that perform the same function will be discussed within. Failure modes and effect analysis (FMEA) is a form of qualitative analysis to determine the single-equipment failure modes and each failure mode's effect on the system. A failure mode and effects analysis (FMEA) was produced for the current CRDMs Table 3, the new CRDMs Table 4, and a comparison between the two was produced shown in Table 7.

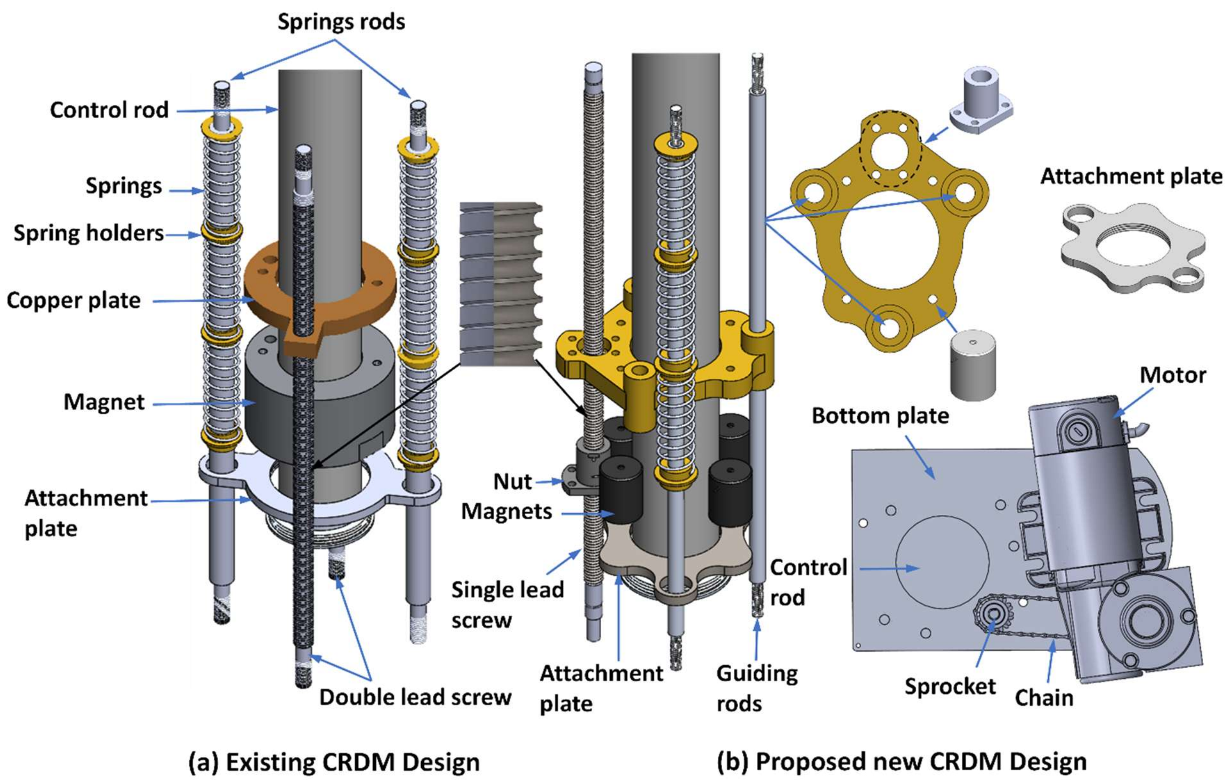

Figure 2. Comparison of the current and new designs. [5]

2.3.1 Current Control Rod Drive Mechanism Design

2.3.1.1 General Description

The AGN-201m is equipped with four near-identical CRDMs containing "20 grams of core material" [4]. All four control rods are comprised of two chain-driven leadscrews connected to a motor at the bottom of the assembly. The fine and coarse CRDMs use an encoder for position indication driven by a second chain connected via a sprocket to the motor. In the rods current form there is a risk of rod drive malfunction causing loss of the ability to control reactivity due to binding of the two leadscrews on their chain, but the reactor is still capable of SCRAMming as needed regardless of any malfunction. Figure 3 shows the current CRDM double leadscrew design.

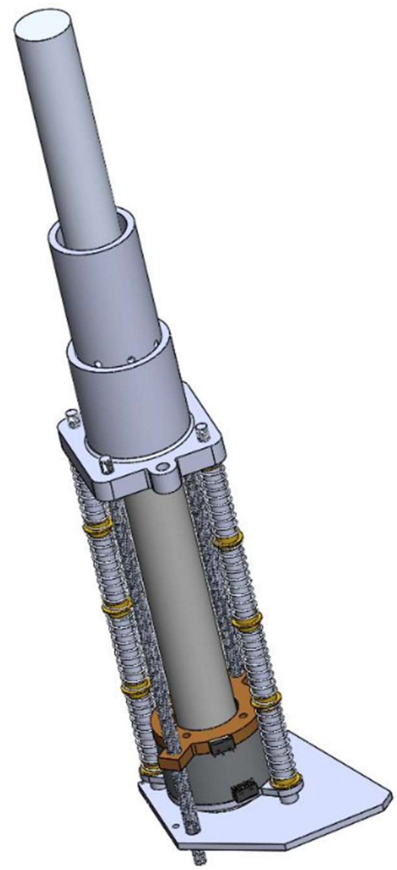

Figure 3. SOLIDWORKS model of current double leadscrew design.

2.3.1.2 Current CRDM FMEA

An FMEA was produced for the current CRDM. Within the FMEA, there are five key electromechanical components that perform a specific function. The FMEA provided the requirements of each component within the scope of failure previously discussed and within the scope of what is discussed in the licensing documentation [3, 4]. The FMEA for the current CRDM can be seen in Table 3.

Table 3. FMEA of the Current CRDM

Item	Description of Use	Failure Modes	Effects	Protections	Actions
Motor	Motor rotates leadscrews for vertical motion.	Motor Fails to start movement downwards Motor Fails to run while moving down	Loss of motor movement causes the loss of vertical motion of the copper piece and electromagnet.	Auditory motion of the chain system Position indication on the copper piece Up and down sensors attached to the brass piece	Loss of magnet current ensures ejection from reactor core Physical removal of power from the reactor console
Electromagnet	Electromagnet connect copper piece and magnet plate together	Electromagnet fails to remain engaged during reactor operation outside of a SCRAM environment	Rods do not swiftly eject from core from SCRAM provided power is not removed	Contact indication on the console via the engaged light. Magnet current display on console in mA.	Physical removal of power from the reactor Motor & magnets are connected in series; loss of electrical continuity one forces the loss of the other
Microswitch	Microswitch depresses at limits (upper, lower, engaged) to provide signal to console	Microswitch fails to provide signal Microswitch fails to depress when reaching limit	Loss of microswitch functionality removes position indication at upper or lower bound. Operator is unable to insert rod if control	Component is informative to position limits (up, down, engaged) but not for precise CRDM position	Loss of electrical circuit guarantees a SCRAM These components do not prohibit SCRAM events nor

Item	Description of Use	Failure Modes	Effects	Protections	Actions
			rod drive and control rod are not engaged.		influence the SCRAM System
Leadscrews	Leadscrews allows for vertical motion of the reactor control rods in conjunction with the motor	Leadscrews bind causing the inability to withdraw the copper piece from the reactor core	Copper piece is jammed in the upper position	Lubricant to reduce friction Position indication on the console attached to chain system.	Loss of electrical circuit guarantees a SCRAM Physical removal of power from the reactor console
Encoder	Encoder physically coupled to the chain linkage system allowing for vertical motion between the motor and the leadscrew	Encoder fails to transmit signal from CRDM chassis to console Component becomes decoupled from the brass piece	Operator is unable to determine precise position, but is still able to determine whether at lower or upper limit	Only records position of brass piece meaning control rod drive SCRAM is independent of this component	Loss of electrical circuit guarantees a SCRAM These components do not prohibit SCRAM events nor influence the SCRAM System

2.3.1.3 Dimensions

The total height of the CRDM from the bottom of the leadscrews to the top of the brass plate is 23.30 inches allowing for a total travel distance of about 25 cm [3]. The current CRDM has a length and width under 8 in allowing for the installation of all four CRDMs below the AGN-201m reactor.

2.3.1.4 Components

The AGN-201m contains three microswitches per CRDM, totaling to twelve microswitches for all four assemblies. The microswitches provide important limiting information to the operator. There is one microswitch attached to the top of the brass plate; the microswitch is responsible for sending the up signal to the control console and electronically stopping further upward motion. The second microswitch is connected to the bottom of the brass plate aside from the magnetic plate; it is responsible for relaying the down signal to the operator and prohibiting further downward movement. The last microswitch is on the side of the brass plate such that it is depressed by the magnetic plate when the electromagnets are active; it relays the engaged signal and is required to be depressed to allow for any movement of the control rod drive chassis. Figure 4 shows a CAD drawing of the microswitch used in the current design.

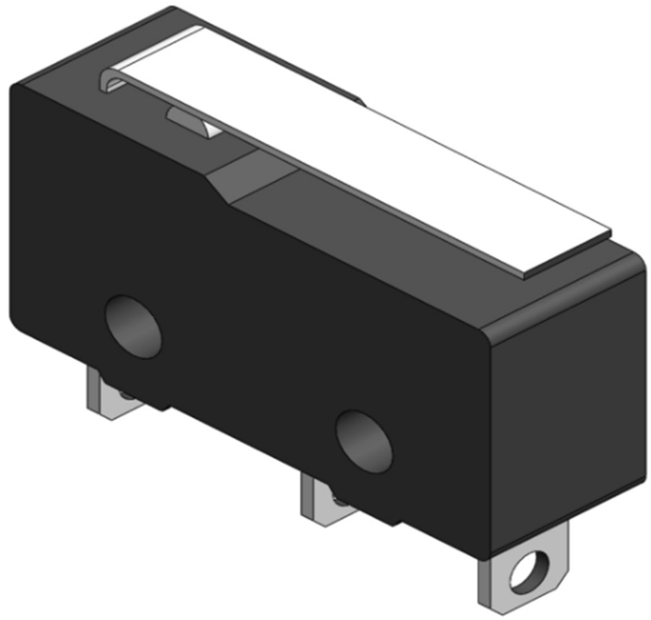

Figure 4. Microswitch used in current design [1].

The chain setup of the current CRDM uses two linkages, one connects the leadscrews to the motor, one connected to the sprocket driving the encoder. The rod drive mechanism is raised by the rotation of both leadscrews. Figure 5 shows the chain routes, excess slack causes notable lag between each leadscrew, the motor, and the encoder. The risk of the CRDM binding increases over time typically requiring correction at least annually.

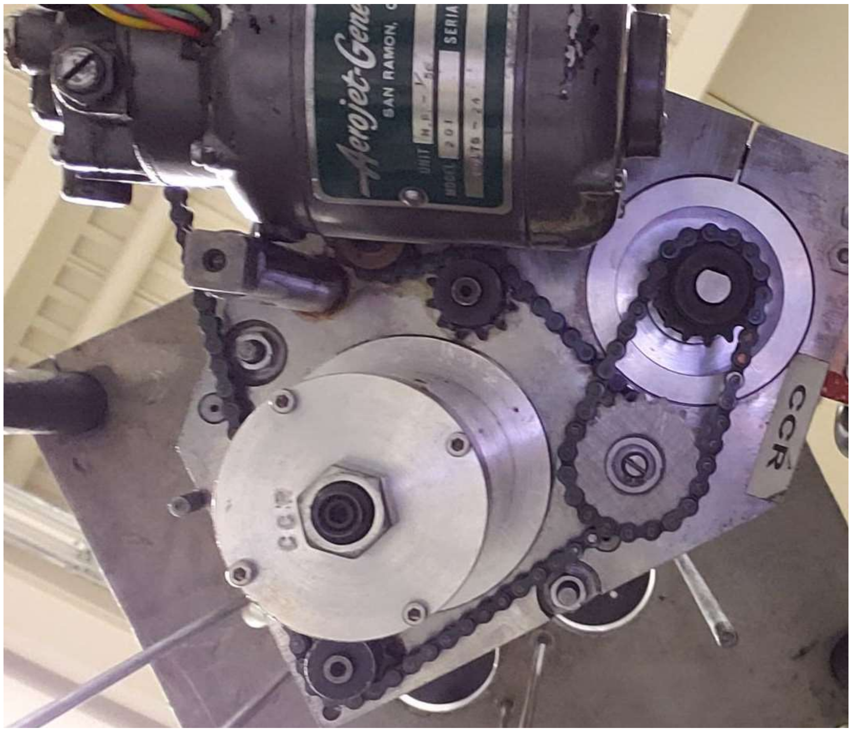

Figure 5. Bottom view of the current CRDM.

During a SCRAM event the rods are ejected from the core within approximately 120 milliseconds for each SCARAM-able rod [3]. To prevent damage to the rod drives and the fuel within, each SCRAM-able rod is equipped with pneumatic dashpots to soften the landing of the canisters as the ejection occurs [3]. These dashpots are effective at deceleration of the control rods or safety rods during the last 10 cm of travel [3]. The dashpot for the CRDM will not be upgraded in the new design.

The leadscrew used in the current CRDM is a standard threaded screw type. The leadscrew is coupled to the motor via the aforementioned chain linkage; the connection allows for vertical movement to be supplied to the main brass piece of the control rod drive chassis. The leadscrew allows for approximately 25 cm of vertical movement. The standard threading of the leadscrew must be lubricated and inspected annually.

The current CRDM utilizes the original Aerojet General Nucleonics brand reversible 24 volt brushed DC motors connected in series [3]. Each motor is connected to the leadscrew via a chain and sprocket linkage allowing for around 25 cm of vertical movement [3]. The maximum removal rate of the SCRAMed rod drive chassis is approximately 0.5 cm/sec [3]. Figure 6 shows the course control rod (CCR) motor within the reactor core.

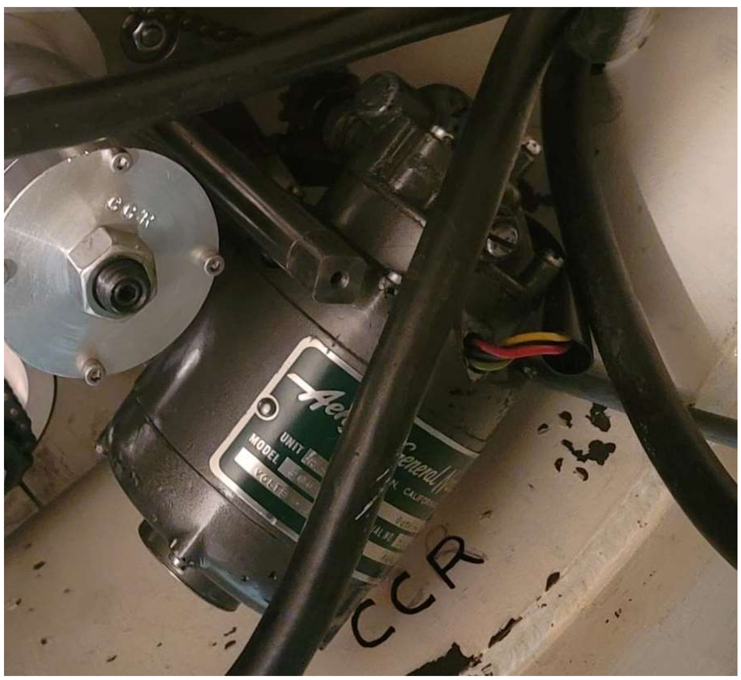

Figure 6. Image of CCR motor within the reactor.

The springs currently used within the current CRDMs were determined previously by a senior design group to be 4.6 lbs/in [1]. Table 4 shows the experimental results of how the spring constant was calculated using displacement and compression of the springs under a measured load.

Table 4. Spring Constant Determination Data [1]

Mass [g]	Force [N]	Compression [in]	Compression [mm]	Displacement [in]	Displacement [mm]
0	0	3.75	85.725	0	0
500	4.903325	3.0625	77.788	0.3125	7.9375
1000	9.80665	2.8125	71.438	0.5625	14.2875
1500	14.70998	2.625	66.675	0.75	19.05
2000	19.6133	2.5	63.5	0.875	22.225

The current CRDM utilizes two digital rotary encoders on the two control rod drives, the coarse control rod, and the fine control rod [3]. These encoders are connected to the console's center panel [3]. The updated rotary encoders used currently are an upgrade upon the original synchrogenerator. The rotary encoders were found to be more precise than the original synchrogenerators, reducing the need to adjust the readout display on the console.

The current electromagnet couples the rod drives and magnetic plate to the rest of the chassis and allows for the vertical movement in conjunction with the motor, leadscrew, and chain setup. The electromagnet is responsible for SCRAMing the reactor when necessary and the SCRAM interlock system ensures the SCRAM functionality is maintained. The SCRAM interlock system is not being modified outside of the implementation of newer electromagnets.

2.3.1.5 Materials

The current CRDM is made of steel for the top and bottom plates and structural supports providing adequate strength. The piece holding the electromagnet and spring holders were constructed out of brass. With the electromechanical components and necessary wiring, the total weight of one current CRDM was determined to be approximately 40 lbf [1].

2.3.2 New Control Rod Drive Mechanism Design

2.3.2.1 General Description

The new rod drive design started as a project in 2017 to upgrade the rod drives to a lighter weight material to reduce the hazard of performing maintenance on the rod drive mechanisms and an attempt to reduce issues with leadscrew binding issues. The overall design exchanges substantial amounts of steel parts for high strength aluminum components and provides many of the other components with a new replacement part to refresh the overall parts and ideally reduce maintenance from using aged parts from the 1950s. The design incorporates:

- Change from two leadscrews to a single-leadscrew design to reduce binding between the leadscrews.
- Adding linear motion bearings to reduce risk of binding with the various guide rod tracks.
- Reduce the weight of the design due to the material change.
- Proprietary parts instead of purely experimental to make replacement components easier and standardized.

2.3.2.2 New CRDM FMEA

An FMEA was produced for the current control rod drive mechanism. The new CRDM FMEA includes an analysis on five specific electromechanical components: motor, four electromagnets, microswitch, leadscrew, and linear potentiometer. Table 4 shows the single-equipment failure modes and effects as well as protections and actions to prevent failures of the component.

Table 4. FMEA of the New CRDM

Item	Description of Use	Failure Modes	Effects	Protections	Actions
Motor	Motor rotates leadscrew to allow for vertical motion.	Motor Fails to start movement downwards Motor Fails to run while moving down	Loss of motor movement causes the loss of vertical motion of the brass piece.	Auditory motion of the chain system Position indication on the brass piece Up and down sensors attached to the brass piece	Loss of magnet current ensures ejection from reactor core Physical removal of power from the reactor console
Electromagnet (4x)	Electromagnets connect brass piece and magnet plate together	2 of 4 Electromagnet fails to deenergize when SCRAM is initiated 2 of 4 Electromagnet fails to remain engaged during reactor operation outside of a SCRAM environment.	Rods do not swiftly eject from core from SCRAM	Contact indication on the console Magnet current display on console	Physical disconnection of power from the reactor Motor and magnets are connected in series meaning loss of one should force the loss of the other
Microswitch	Microswitch depresses at limits (upper, lower, engaged) to provide signal to console	Microswitch fails to provide signal Microswitch fails to depress when reaching limit	Loss of microswitch functionality removes position indication at upper or lower bound. Operator is unable to insert rod if control rod	Microswitches are informative to position limits (up, down, engaged) but not for control rod drive position	Loss of electrical circuit guarantees a SCRAM These components do not prohibit

Item	Description of Use	Failure Modes	Effects	Protections	Actions
			drive and control rod are not engaged.		SCRAM events nor do the
Leadscrew	Leadscrew allows for vertical motion of the reactor control rods	Leadscrew fails to withdraw brass piece assembly from the reactor core	brass piece assembly is jammed in the upper position	Lubricant to reduce friction from ball-nut leadscrew design reduces friction on the leadscrew Position indication on the console attached to brass piece	Loss of magnet current ensures ejection from reactor core Physical disconnection of power from the reactor
Linear Potentiometer	Linear potentiometer is physically coupled to the brass piece allowing for indication of vertical position and relays data to the console.	Linear potentiometer fails to transmit signal from CRDM chassis to console Component becomes decoupled from the brass piece	Operator is unable to determine precise position, but is still able to determine whether at lower or upper limit	Only records position of brass piece meaning control rod drive SCRAM is independent of this component	Loss of electrical circuit guarantees a SCRAM These components do not prohibit SCRAM events nor influence the SCRAM System

2.3.2.3 Dimensions

The new CRDM has a total height of 26.84 inches from the bottom of the motor to the top of the top plate's cylinder, allowing for 24.64 inches of rod movement. The total length was found to be approximately 8 inches long [1]. The overall length of the bottom piece is identical to the bottom piece of the current CRDM. The overall width of the CRDM was derived from the motor and was found to be 7.35 inches. Figure 7 shows the single leadscrew design developed by the senior design team.

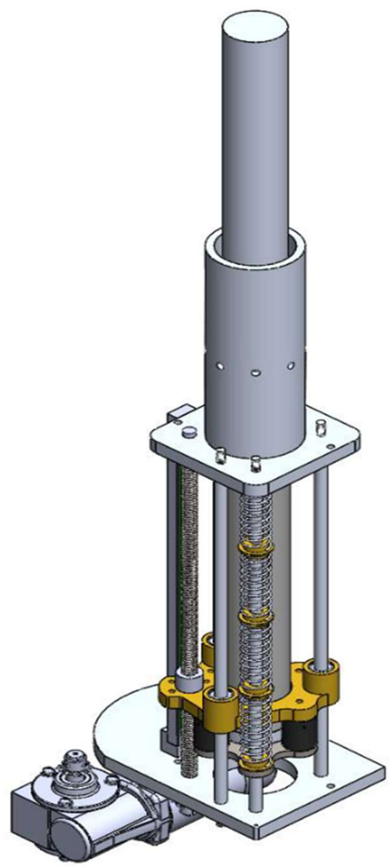

Figure 7. SOLIDWORKS model of the single leadscrew design.

2.3.2.4 Components

The new CRDM will use new but identically functioning microswitches to perform the same actions of limiting the rod's path of motion upwards and downwards.

The current CRDM utilizes a dual chain setup, separating position indication and vertical movement into two chain linkages. The division of chains and variable slack from the act of maintenance causes lag to occur between the actual rod insertion height and the rod insertion height provided to the operator. The new CRDM utilizes a simpler and shorter chain to provide the same function. The position indication is no longer attached to the chain meaning the chain no longer needs to drive both position indication and the movement of the rod drive chassis. Figure 8 shows the proposed simplified chain and sprocket setup used by the new design.

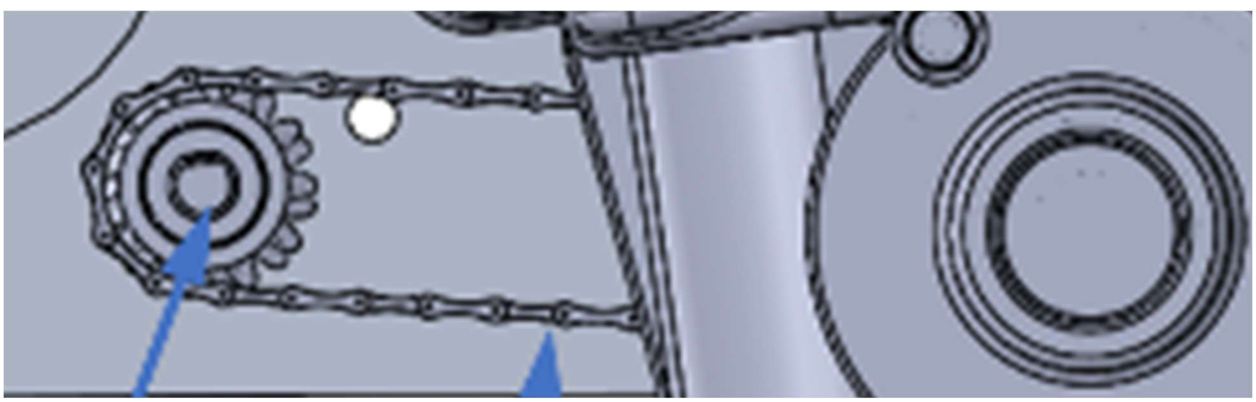

Figure 8. CAD drawing of chain configuration of new CRDM [5].

The new CRDM design utilizes a ball-nut leadscrew design to provide reduced friction and smother vertical manipulations of the control rod drives. The leadscrews are connected to the brass piece along with three supplemental guide rods; these guide rods are connected to the brass piece via linear motion bearings to allow for smooth vertical movement.

The motor for the new CRDM design is a Bodine Model 4694 DV Gearmotor, because the current CRDM motors were made by Aerojet General Nucleonics and are therefore no longer produced. The new motor aims to remain as a reversible brushed 24 Volt DC type. The new motor is rated up to 10 lb-in of torque and a possible rotation speed of 250 RPM [1]. Figure 9 shows a schematic drawing of the Bodine motor in the new design.

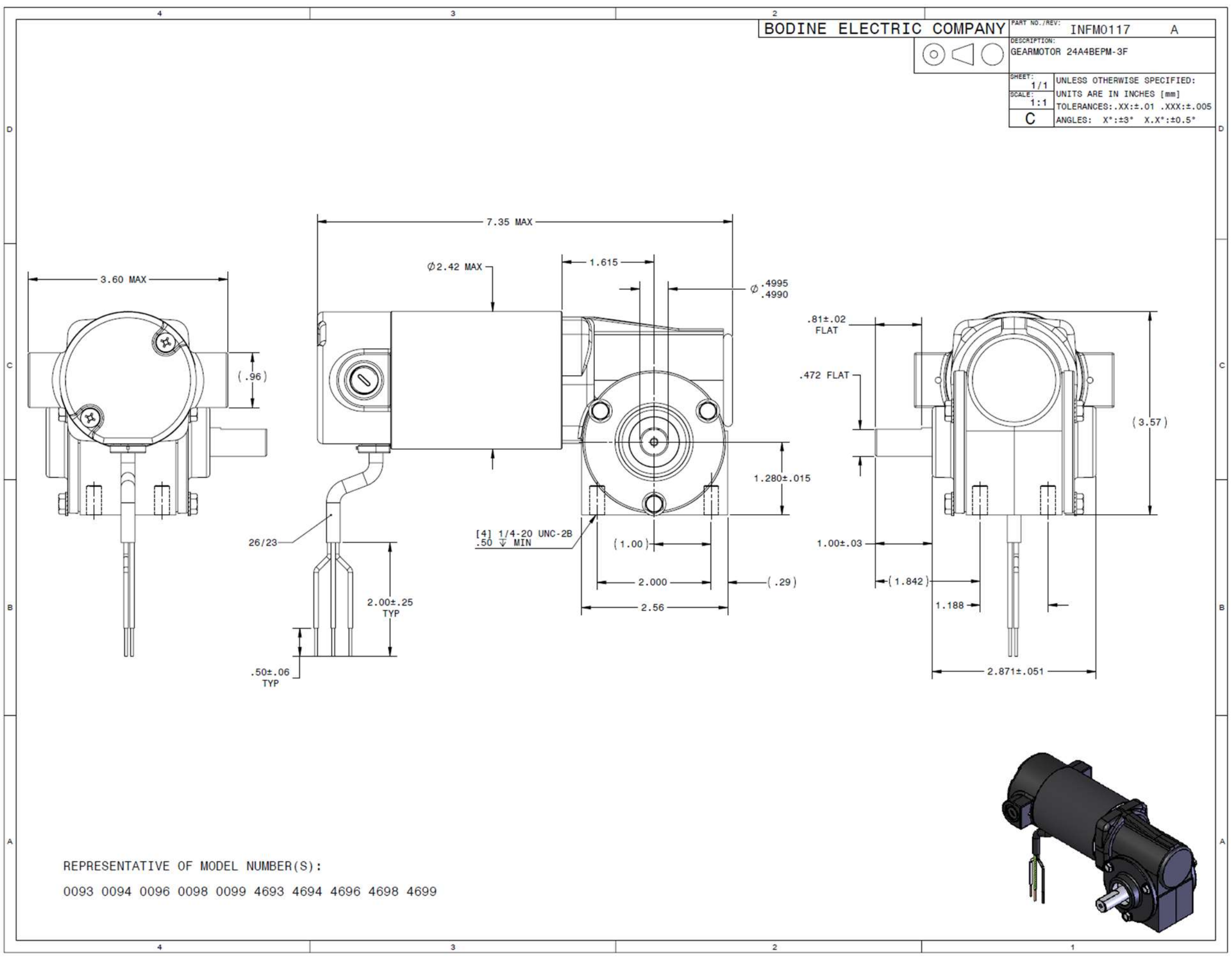

Figure 9. Motor schematics [1].

The springs used in the new CRDM use a spring constant of 4.6 lb/in allowing for a functionally identical capability of the springs within the current CRDM.

The new CRDM replaces the current encoder setup driven by a chain with a more precise linear potentiometer to increase the accuracy of CRDM manipulations. The linear motion potentiometer slide will be physically connected to the brass piece component. The distance traveled by the slide will produce a voltage differential signal to provide position indication for the operator to use for reactivity manipulations. Figure 10 shows the comparative differences between the current and new position indication systems employed by the respective designs.

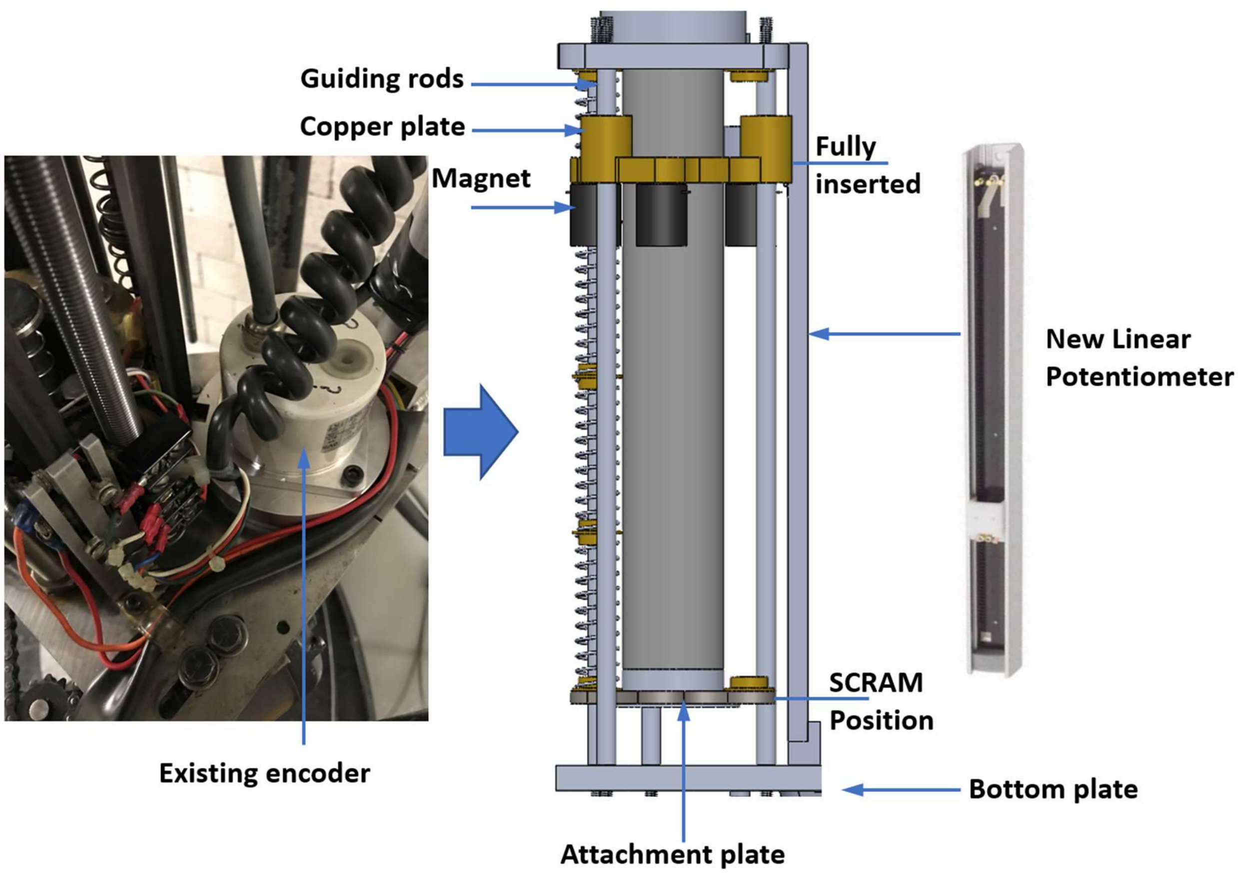

Figure 10. Comparison of the position indication change over.

The new CRDM replaces the single large torus-shaped electromagnet with four smaller cylindrical electromagnets as shown in Figure 11 [1]. Each magnet has a 1 in diameter and a height of 1.25 in.

The electromagnets of each CRDM are connected in series and produce a magnetic pull of 20 lbf each [1].

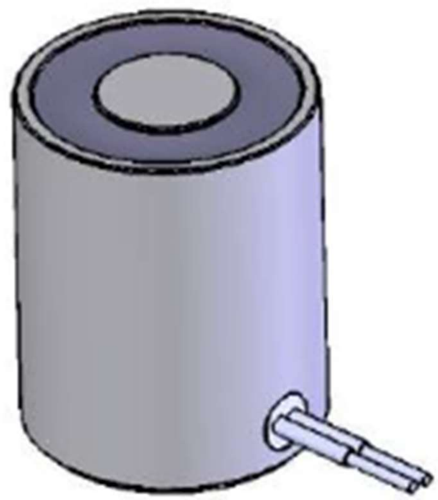

Figure 11. Digital drawing of electromagnet [1].

It was determined that each set of magnets would be required to exceed 31.17 lbf to hold the rods and keep the springs compressed [1]. A factor of safety of 2.51 determined each rod drive mechanism would require 80 lbf. The factor of safety ensures the magnet will be able to sufficiently hold the control rod drive in the most reactive position without risk of the magnet and magnetic plate becoming uncoupled outside of a SCRAM event.

2.3.2.5 Materials

The new CRDM design utilizes Aluminum 6061-T4 for the top and bottom plates and the structural guide rods. The new design also incorporates brass for the spring dividers, and a brass piece holding the magnets to the rest of the chassis. The control rods or safety rods will be physically connected to a threaded magnet plate constructed from stainless steel to allow for appropriate magnetism to maintain adequate SCRAM-ability. The total weight of all components was found to be 20.7 lbf [1].

2.3.2.6 Cost of New Rod Components

At the time of the project instantiation, the components for a single CRDM was projected to cost \$6,408 as is shown by Table 5 and Table 6 from many undeclared vendors. As of 2021, the cost of one CRDM was determined to be \$4,179.75 from various manufacturers shown in Table 5 and Table 6. The NEUP Grant provided \$59,262 funding allocated to component procurement, and potential testing equipment. The NEUP Grant value covers materials, services, and indirect costs [2].

Table 5. Electromechanical Component Costs for a Single CRDM

Item #	**Component**	**Brand / Model Number**	**Estimated Unit Cost**	**Number of Items**	**Total Cost**	**Purchase Price**
1	Reversible DC Motor	Bodine 24A-3F Series DC Right angle Gear Motor Model N4894	$402	1	$ 402.	$416.82
2	Motor Mount /Control /Accessories	24A Brush cap – Part Number 49300037 24A Brush and Spring – part number 49201001 Base plate mounting kit for 3F gearmotors [model 0967]	$196	1	$ 196.	$35.69
3	Motor Sprocket, Leadscrew Sprocket	B&B Manufacturer Model 25BF14x1/2 Roller Chain Sprocket	$15	2	$ 30.	$18.4
4	Motor Chain*	Duty Plus #25 Roller chain-10 FT BOX	$35	1	$ 35.	$27
5	Springs	The Spring Store: PC067-540-17600-MW-3000-CG-N-IN	$16	8	$ 128.	$44.8
6	Electromagnet	Buy Magnet BDE-1012-12	$25	4	$ 100.	$104
7	Linear Motion Conductive Plastic Potentiometer**	P3 America Inc. Motion Control and Automation Products	$465	1	$ 465.	$465
8	Microswitches	Omron SS-5GL – Microswitch Subminiature hinge Lever SPDT Solder, 5 A.	$5	3	$ 15.	$5.10
9	Ball-Nut Leadscrew	NOOK PMBS12x2R-3FW/0/T10/1K/2K/406/1/S	$1200	1	$1,200.	1048
		Subtotals			$2,571.	$2,165.

* 10 ft per box can be shared between rods.   ** the model selected is the 610 mm stroke/10k ohm

Table 6. Bulk Metals and Machining Costs for a Single Drive

Item #	**Component**	**Description**	**Estimated Unit Cost**	**Number of Items**	**Old Total cost (2017)**	**Purchase Price (2020-2021)**
10	Aluminum slides (high Strength)	2 Spring Rods and 3 guide rods – 16” length	$55	5	$275	N/A
11	Brass plate	Brass Disc to carry the electromagnets and nut for the leadscrew	$600	1	$600	N/A
12	Magnet Plate	Steel Plate to attach to the electromagnets	$62	1	$62	N/A
13	Bottom Aluminum Plate	Drive carrier lower plate	$210	1	$210	N/A
14	Upper Aluminum Plate	Drive carrier upper plate	$190	1	$190	N/A
15	Spring Holder	Hold springs in lace along the guide rods	$14	6	$84	N/A
16	End Spring Holder	Hold springs in lace along the guide rods	$14	4	$56	N/A
17	Linear Bearings	Multiple Bearings for the guide rods and screw	$45	8	$360	N/A
18	Rod Clearance pipe	Aluminum pipe for holding rods in line going from the top & bottom plates	N/A	2	0	N/A
19	Machining Labor	Machine shop cost (items 10 15)	$2000	1	$2000	N/A
		Subtotals			*$3837*	*$2014.75*

2.3.3 FMEA Comparison

To summarize the changes made to the CRDMs with respect to an FMEA evaluation, Table 7 describes the similarities and differences between the critical functions performed by each electromechanical component.

Table 7. FMEA Comparison of Current CRDM vs New CRDM

Item	Physical Differences	Failure Mode Differences	Effects Differences	Protections Differences	Actions Differences
Motor	Same	Same	Same	Same	Same
Electromagnet	The current CRDM has on torus-shaped magnet There are four times the number of Electromagnets in the new	One electromagnet needs to fail in the current CRDM 2 of 4 electromagnets need to fail in the new	Same	Same	Same
Microswitch	Same	Same	Same	Same	Same
Leadscrew	The current CRDM contains two leadscrews of standard threading. The new CRDM contains one ball-nut threaded leadscrew	Overall failure would be the same Current CRDM design has an increased issue with binding due to chain slack & increased friction.	Same	Same	Same
Position Indication Component	The Current CRDM utilizes a digital encoder to provide position indication The New CRDM utilizes a linear potentiometer to provide position indication	Same	Same	Same	Same

2.4 Industry Standard Probability Software

All nuclear engineering focused reliability software are made up of three user-developed models: event trees, fault trees, and basic events. To make the overall challenge of modelling entire facilities streamlined and manageable, computer software is produced to determine the probability of component failures and make changes as more information becomes available. The reliability model of ISU's AGN-201m reactor focuses on the development of high-fidelity CRDM models as it is the only mechanical system presented controlling reactor power.

2.4.1 Event Trees

An event tree encompasses the path of response systems within a facility. Event trees are derived from a particular initiating event and how a facility's systems are impacted by said event. Event trees are oriented such that failures of systems move downward [6].

Per the AGN-201m Safety Analysis Report, any credible event will induce a SCRAM and allow the reactor to remain subcritical by exceeding the shutdown margin of 1 % $\Delta k/k$ [4].

Event trees are generated through the systematic approach of categorizing the broad stroke systems within a facility and recording how they must respond, or fail to respond, and what the outcome of said events would be when analyzing the facility.

2.4.2 Fault Trees

A fault tree is a collection of logical gates, basic events, and numerous failure probabilities; these are representative of the of a system that impacts the overall facility functionality in some way. Fault trees represent a system, or a group of systems used to perform a particular task.

Fault tree generation requires adhering to an analytical technique of identifying the undesirable and quantifying the likelihood frequency as a probability to inform operators, regulators, and license holders of the high importance event to regulate [6].

2.4.3 Basic Events

Basic events are employed to show a singular component as part of a larger system or upset. These events can encompass human performance reliability, failure to begin a task, failure during a task, etc. For the scope of the project, human reliability, and failure to start or perform a task are the only failure types of pertinence. Basic events serve as the primary building block used by nuclear reliability software and serve as the uncategorized form of holding data.

2.4.3.1 Common Cause Failure Events

Basic events serve as the foundational building blocks to fault trees and event trees; as a result, facilities will likely have multiple of the same component used for similar or identical functions in a separate fault tree or component. Common cause failure is accounted for with the introduction of common cause events. Either of the two main forms Alpha Factors or Multiple Greek Letters take into consideration factors to provide a probability of failure for multiple components of the same type.

2.4.3.2 House Events

House events represent events guaranteed to happen or not happen based on the configuration. The most common house event employed in industry claims all facilities with multiple system trains will never have more than one be out for testing or maintenance at the same time. House events are used to exclude certain mutually exclusive events or investigate the facility's probability of failure from removing a particular basic event.

2.4.3.3 Human Reliability Calculations

Human reliability events cover in a general sense an operator's ability to perform, diagnose, or otherwise react to the reactor event. Human reliability relies on various factors to performing the task such as: available time, stress, task complexity, experience or training, procedures available, ergonomics, fitness for duty, and work processes.

Chapter 3: Materials and Methods

3.1 System Analysis Programs for Hands-on Integrated Reliability Evaluations

The NRC utilizes a reliability software to model their licensed plants; the regulatory software used is the System Analysis Programs for Hands-on Integrated Reliability Evaluations (SAPHIRE), the version used for this model is SAPHIRE 8, as a result use on older versions may not function as intended.

The SAPHIRE software is a fault and event tree graphical editor which includes cut set generation, quantification, importance measures, and uncertainty modules to allow for more robust metrics. SAPHIRE is a relational database system which cross-references features and allows for external events analysis. Traditionally, SAPHIRE is used for rule-based recovery and end-state analysis of common cause failure events [7].

3.2 Python Script Data Analysis

As part of determining the failure probability of the current CRDM components, a machine learning approach was used to determine an approximate failure of the CRDMs as an integrated system. A dataframe of data from annual report data and feature engineering was created to provide usable data for machine learning.

To ensure the best results, the project aims to use various different machine learning methods to determine the optimal method for finding the actual failure rates for all important components. The dataframe used started with 123 entries of a date and a description. Once all data was parsed and sifted through the dataframe contained 119 entries with 26 features. As shown in Table 8, the data obtained from Annual Reports were mainly qualitative in nature and required extensive pruning to produce a machine learning usable dataset as seen in Table 9. In Table 9, a 1 indicates a component failure and a 0 indicates nominal operational status. The total failures of each of the component subsystems were obtained by summing the failures in the dataframe.

Table 8. First Five Rows of the Unchanged Dataframe from Annual Report

Date Performed	Description[3]
02/05/2010	During start up the reactor SCRAMed and all rods dropped out; but the SR-1 magnet chassis did not drive down. After significant trouble shooting it was found that the magnet collar was worn and that the grub screws were adjusted slightly off from each other. The SR-1 magnet had become weak and developed a short in the system; so it had to be replaced. In order to accommodate the replacement AGN magnet the brass collar was slightly modified to allow for wiring. The last of the problems with SR-1 were addressed on 4/14 when the rod indication micro-switches were slightly adjusted to engage with the rod drive chassis.
03/03/2010	One of the fuses in Channel 2 was found to be blown. When the fuse was replaced, the V-12 6BW4 vacuum tube in Channel 2 was found to be arcing. The vacuum tube was replaced, and the channel tested successfully.
04/21/2010	The Channel 1 detector release solenoid was malfunctioning and temporarily released mechanically. The solenoid was found to have a weak solder joint that was repaired.
06/09/2010	It was found that a number of Channel 2 & 3 potentiometers were weakened from age. Appropriate replacements were found and installed on the Channel 1 internal calibration; Channel 2 10-7; 10-11; infinity; and + period potentiometers. Calibration procedures were performed on both channels the following day.
08/19/2010	The fine control rod was driven up into the full up position but could not be driven back down. The rod drive chassis was removed and tested in the experiment stand. The situation could not be reproduced, and the drive was re-installed in the reactor. The drive tested successfully multiple times in core.

[3] Available online at: https://gitlab.com/WickedWess/cs-final-rod-drive-risk/-/raw/main/Decade_Compilation2010-2020.csv

Table 9. First Five Rows of the Pruned Dataset Usable by Python

Rod Drive Failure	Motor Failure	Magnet Failure	Lead Screw Failure	potentiometer failure	Microswitch Failure	Console failure	Detector Failure	Channel 1 Failure	Channel 2 Failure	Channel 3 Failure
1	0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0
0	0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	1	0	0	0	0
1	0	0	1	0	0	0	0	0	0	0

One of the most useful visual aids for the machine learning model was the development of a correlation heatmap. Figure 12 shows the correlation of features used by the model. As shown, the total failures of a certain component and the individual failures of a certain component are highly correlated whereas there is a natural low correlation between independent components such as the console and the reactor CRDMs.

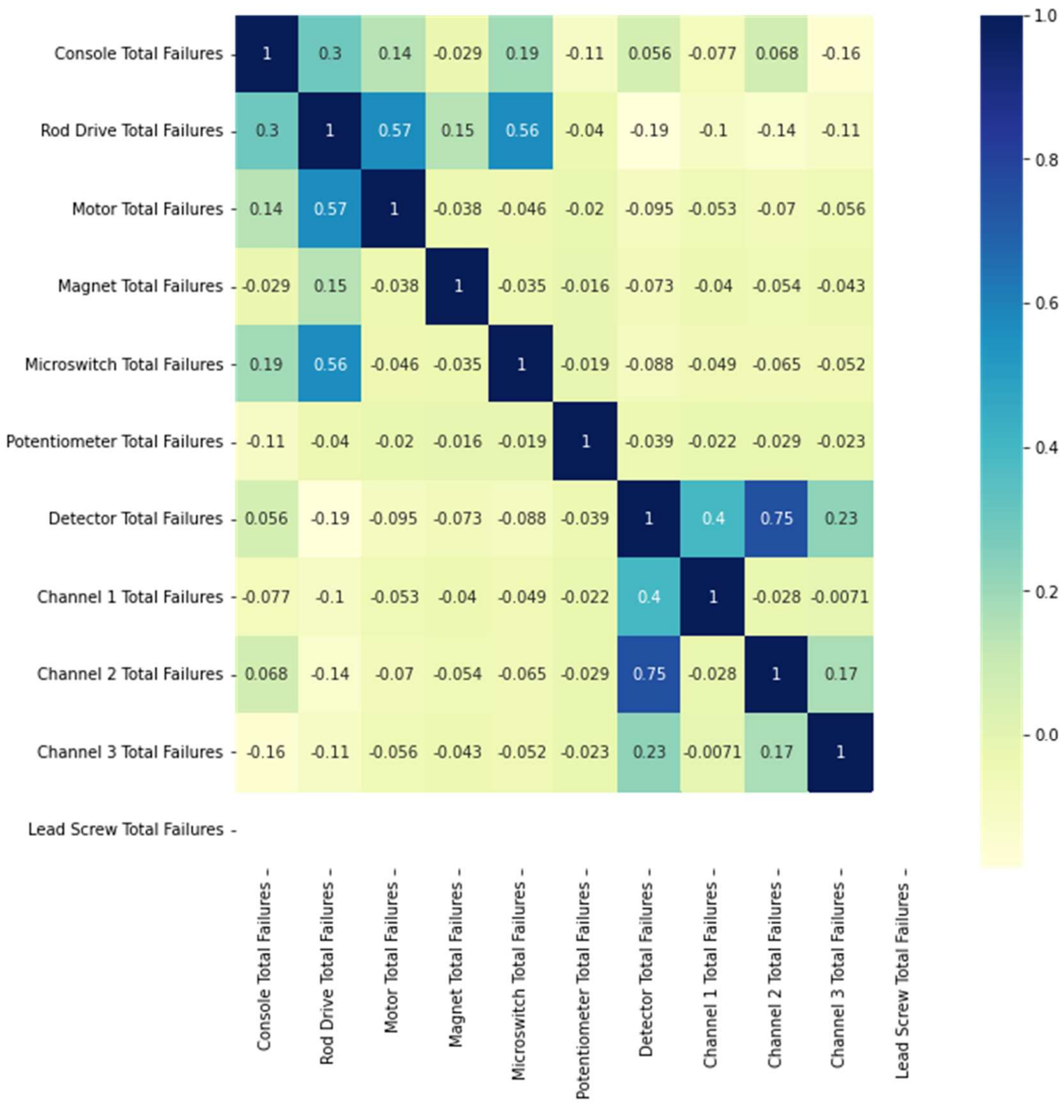

Figure 12. Dataframe correlation heatmap.

3.2.1 Maintenance Log Cleaning

The unmodified dataframe supplies the description and date that maintenance was performed. Each entry was pulled from the Annual Reports from 2016 to 2020. Preprocessing was necessary to get a set of unique features that can be used by machine learning algorithms. Some engineered features used and developed were:

- Rod Drive Failure
- Motor Failure
- Magnet Failure
- Leadscrew Failure
- Potentiometer Failure
- Microswitch Failure
- Console Failure
- Detector Failure
- Channel One Failure
- Channel Two Failure
- Channel Three Failure
- Solution of Maintenance
- New or old Console

Many, if not all, of these features can be parsed from the information within the description; and with the dataset as large as it is the process was conducted manually through Excel. The dataframe initially had all the data configured as Boolean values but were later converted to numerical equivalent binary integers of zero and one, as a component cannot partially fail due to the overall simplicity and function of each component.

Many of the manually parsed features are Boolean values, where the total failures of each major category of component was tallied. The features listed below were tallied up to determine the total number for their respective component.

- Total Rod Drive Failures
- Total Motor Failures
- Total Magnet Failures
- Total Leadscrews Failures
- Total Potentiometer Failures
- Total Microswitch Failures
- Total Console Failures
- Total Detector Failures
- Total Channel One Failures
- Total Channel Two Failures
- Total Channel Three Failures

Creating totals implied mutual exclusivity of the standalone failures.

An important distinction between this data set and the actual answer is that the data set being collected using annual report instances allow for a quick development of the dataframe at the cost of being objectively incomplete. Due to only maintenance and failures being logged in the annual report, the probabilities are based on the condition of maintenance occurs whereas in actuality, some events do not require maintenance.

3.2.1.1 k-Nearest Neighbors

The first machine learning algorithm implemented was k-Nearest Neighbors (KNN) using SciKit-Learn's `KNeighborsClassifier()`, KNN is commonly used for classification problems. By generating a random point within the graph, the KNN algorithm determines the 'nearest neighbors' to the point to determine what the random point would be. To determine the closest neighbors, the Minkowski distance formula shown in the equation below is used, where $p = 2$ by default (Euclidean distance). If K = 1, the algorithm finds the closest neighbor to determine the point's type.

$$d(X,Y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}} \tag{2}$$

KNN does not require splitting the data set for training and testing, thus allows for the use of the entire dataframe, this advantage was not used to allow for a fairer comparison between the other models. With an increase of data from an actively used reactor, acceptable results through machine learning can be applied in PRA.

To understand the implementation of a KNN algorithm, a dataset of five fruits is given in Figure 13 where fruits are based off of their sweetness rating of 0-1 on the y-axis and their rarity in a grocery store from 0-1 on the x-axis. To categorize and determine the probability of a given fruit being otherwise a green apple, durian, blackberry, banana, or blueberry, KNN can be used to build a mathematical model to separate the data points out into categories and predict future fruits categories.

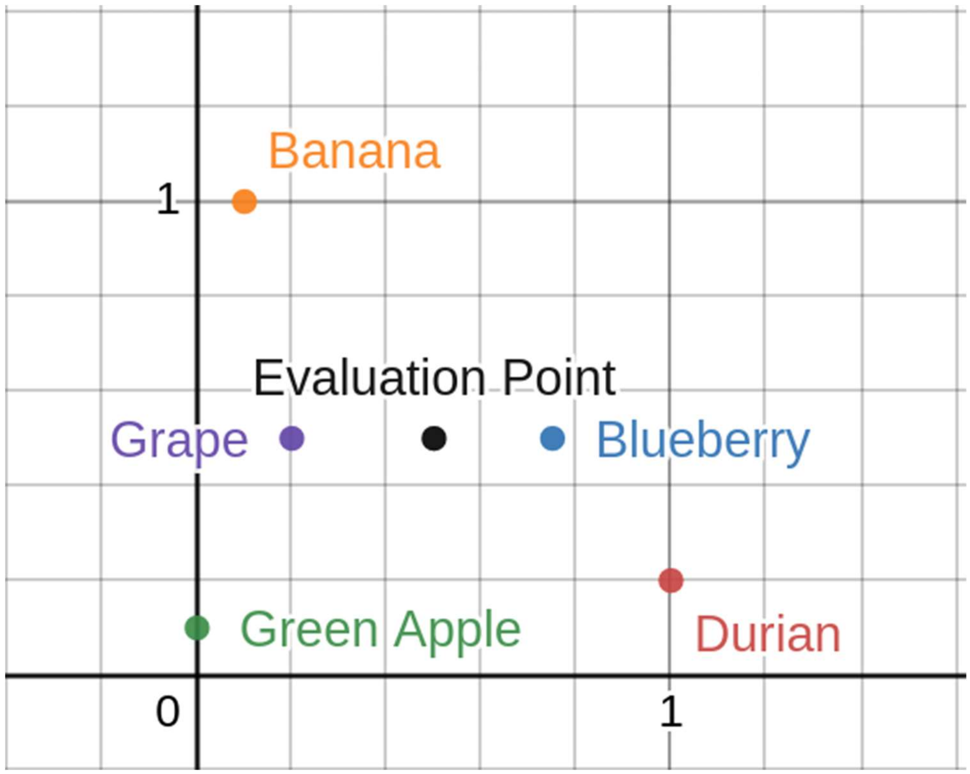

Figure 13. Fruit types plotted based on rarity and sweetness.

To classify the bounds between each type of fruit, a random evaluation point is created to classify. The nearest neighbors specified in the algorithm determine the type of fruit at the evaluation point. In this case, K=1, meaning only the nearest neighbor is considered. Using the Euclidean distance formula, each distance between the evaluation point and the known fruit points are calculated as shown in Table 10 where ultimately the evaluation point was determined to be a blueberry due to blueberry being the closest point.

Table 10. Fruit Euclidean Distance from Evaluation Point

Fruit	Distance from Evaluation Point
Banana	0.30
Green Apple	0.30
Grape	0.40
Blueberry	0.25
Durian	0.40

The process of generating a random point and using the distance formula to determine the closest neighbor is repeated thousands of times, where if the distance from the evaluation point is equidistantly spaced between two nearest neighbors, in a K=1 scenario, the point would be disregarded and regenerated. Eventually, the KNN algorithm will create a probability distribution of the probability that a given random fruit will be otherwise a banana, green apple, grape, blueberry, or durian based off the rarity and sweetness.

3.2.1.2 Logistic Regression

The second machine learning algorithm used was a logistic regression algorithm. Logistic regression provides a linear model capable of classification. Logistic regression can predict the likelihood of an event occurring which shows great promise for further applications of PRA within a nuclear facility. If the dataframe is appropriately related to the overall performance of the model it should be more than capable of yielding an accurate prediction.

Logistic regression is a logistic distribution which uses weighting functions to produce probabilities that have a linear relationship to feature values. Logistic regression fits values on a sigmoid curve as seen in the equation below, where the probability of failure, P is given as a combination of weight functions β_0 and β_1 of the feature matrix $\boldsymbol{X}$.

$$f(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \tag{1}$$

Where β_0 can be calculated using the mean of the sample μ and $\beta_1$can be calculated using the standard deviation of the sample s.

$$\beta_0 = \mu\beta_1 \tag{2}$$

$$\mu = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{3}$$

$$\beta_1 = \frac{1}{s} \tag{4}$$

$$s^2 = \frac{1}{N-1}\sum_{j=1}^{N}\left(x_j - \mu\right)^2 \tag{5}$$

As an example, logistic regression can be used to predict the probabilities of an animal being a bird (1) versus a lizard (0) based on their weight. Two data points of a lizard weighing 19 g versus a bird weighing 60 g, and a test point of 35 g is tabulated in Table 11.

Table 11. Weight of Lizard versus Bird

Weight (g)	Is the object a bird
19	0
35	?
60	1

By applying the logistic regression equations, the resultant distribution and weight parameters are shown in Table 12.

Table 12. Logistic Regression Parameters

Parameter	Value
μ	38.033
s	20.618
β_0	1.8447
β_1	0.0485012

Graphically, the logistic regression model does not fit the dataset well due to the lack of features and datapoints. As seen in Figure 14, the logistic regression line of fit does not intersect with bird, lizard, or the unknown data point.

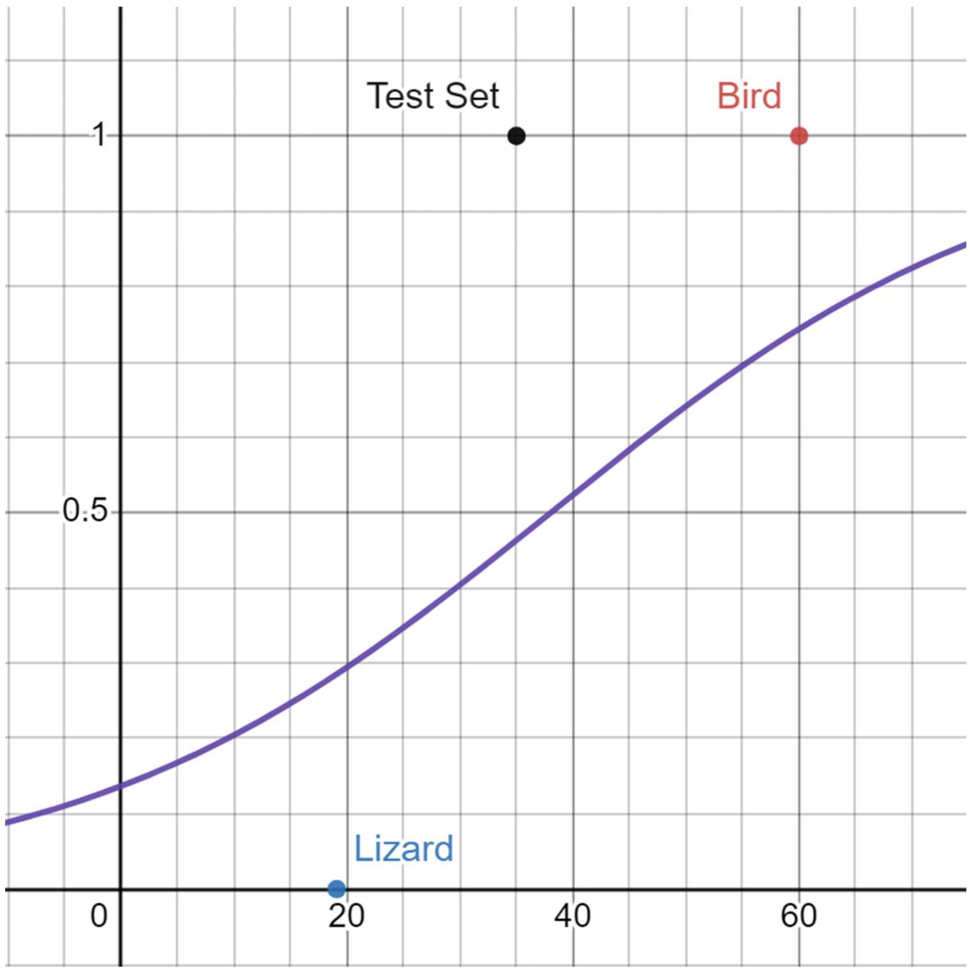

Figure 14. Logistic regression model of birds verus lizards dataset.

The resultant probabilities of each data point being a bird is given in Table 13, where despite the bird data point bird and the test set having a y-value of 1 on the graph, the calculated probabilities of each data point of being a bird is 0.7437 and 0.4633, respectively. These probabilities indicate the low fidelity of the model on a small dataset.

Table 13 Probabilities of a Datapoint being a Bird

Point	P(B)
Lizard	0.2853
Bird	0.7437
Test Set	0.4633

3.2.1.3 Naïve Bayes

The last family of algorithms applied were three different naïve bayes algorithms, each with three different individual use cases. Bayesian Inferencing is an archaic method of machine learning, but Naïve Bayes is still often used in the realm of PRA in other software such as OpenBUGS for Markov Chain Monte Carlo modelling. In that same vein, a Bayesian model performs in similar methods to how an individual would apply Bayesian Inferencing but on a larger scale. Within the project three forms of Naïve Bayes models were used: Gaussian Bayes, Bernoulli Bayes, and Multinomial Bayes. Shown below is the general form of Naïve Bayes calculations.

$$P(y|x_1, x_2, \dots, x_n) = \frac{P(y) \times P(x_1, x_2, \dots, x_n|y)}{P(x_1, x_2, \dots, x_n)} \tag{6}$$

To apply Bayesian statistics within machine learning, the dataframe and the chosen model must be of a related distribution to the data in order to the same distribution to generate accurate results. The results will skew answers that do not fit the assumed model, reducing the accuracy and making the model perform poorly; some of the models used demonstrate this limitation effectively. By incorrectly fitting the dataframe's distribution with the wrong machine learning model distribution, the results are skewed.

3.2.1.3.1 Gaussian

The first form of Bayesian inferencing performed was the Gaussian Bayes machine learning model. As the name implies, the SciKit-Learn `GaussianNB()` model applies a Gaussian distribution to the conditional given predicter event. The Gaussian naïve Bayes modified conditional is shown below:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma^2}} \times e^{\left(-\frac{(x_i - \mu_y)^2}{\times \sigma_y^2}\right)} \tag{7}$$

3.2.1.3.2 Bernoulli

The second Bayesian model used a Bernoulli relation between the conditional and the predicter. The Bernoulli is a special case of the binomial distribution using a single trial. The specific relation is shown below:

$$P(x_i|y) = P(i|y) \times x_i + \big(1 - P(i|y)\big) \times (1 - x_i) \tag{8}$$

The specific implementation was through SciKit-Learn `BernoulliNB()` model. Bernoulli requires that the data provided is binary, as the dataframe used is represented with a binary values, the implementation of Bernoulli Bayes convenient.

3.2.1.3.3 Multinomial

The last model of Bayesian inferencing utilized a multinomial conditional. The multinomial is a derivative form of the binomial distribution. The implementation used was SciKit-Learn `MultinomialNB()`:

$$P(x_i|y) = \frac{N_{yi} + \alpha}{N_y + (\alpha \times n)} \tag{9}$$

3.2.1.3.4 Example of Bayesian Machine Learning

To show Naïve Bayesian predictions in a simpler example, the probability of rain, probability of the weather being cloudy, and the probability that the day is windy will be used. The fundamental work will depend on the assumed relationship between each parameter; for simplicity an example, the data will be collected over a three-month period. For this example, the following assumptions are made:

- Independence is assumed between the three probabilities.
- Independence is assumed between the three experiments.
- The assumed relationship will be gaussian
- Events are not mutually exclusive
- The Gaussian maximum likelihood estimators are:

$$\mu_{MLE} = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{10}$$

$$\sigma_{MLE}^2 = \frac{1}{N}\sum_{j=1}^{N} \left(x_j - \mu_{MLE}\right)^2 \tag{11}$$

Table 14 will function as the dataframe to determine the probability of rain given the parameters on average over this 3-month average. The calculations are performed by determining the maximum likelihood estimator of the parameters based on the assumed relationship as covered by the preceding assumptions. Table 14 covers the features that will be used to make predictions; the features are understood not to be mutually exclusive. For the example the hand algorithm will utilize months one and two as a training set. Accuracy tests will be omitted as the sample size of the dataset is better for the pedagogical value as opposed to creating a good model.

Table 14. Total Number of Rainy, Cloudy, and Windy

Month	**Total Rain**	**Total Cloudy**	**Total Windy**
Month one	4	9	9
Month two	1	12	20
Month three	13	0	15

Using the Gaussian maximum likelihood estimators' equations above and using month one and two's data, the resultant μ and σ^2 values are Table 15.

Table 15. Gaussian Maximum Likelihood Estimators

Month	**Rain**	**Cloudy**	**Windy**
μ_{MLE}	6.000	7.000	14.667
σ^2_{MLE}	39.000	39.000	30.333

Using the Gaussian maximum likelihood estimators above, the conditional probability of cloudy with rain P(C|R), conditional probability of wind with rain P(W|R), and probabilities of rain P(R), cloud P(C), and wind P(W) are in Table 16.

Table 16. Conditional Probabilities of the parameters

Month	**P(C|R)**	**P(W|R)**	**P(R)**	**P(C)**	**P(W)**
Month one	0.0569	0.0569	0.0607	0.0607	0.0427
Month two	0.0403	0.0052	0.0464	0.0464	0.0453
Month three	0.0403	0.0226	0.0341	0.0341	0.0723

By combining the conditional probabilities P(C|R) and P(W|R) from Table 16, the multivariate conditional probability of weather with rain, wind, and clouds for each of the three months are calculated below in Table 17.

Table 17. Resulting Conditional Probability of Rain Given the Weather is Windy and Cloudy

Month	**P(R|W,C)**
Month one	0.0759
Month two	0.0045
Month three	0.0126

The process for obtaining P(R|W,C) for multinomial and Bernoulli Naïve bayes will be consistent with the Gaussian Naïve Bayes as only the probability density functions will change and thus the maximum likelihood estimators.

Chapter 4: Analysis

4.1 Machine Learning Algorithm Analysis

4.1.1 Model Analysis

Overall, all but one of the algorithms demonstrated the ability to provide highly accurate probability predictions, as shown in Table 18, but all models have been shown to be volatile to variation. This volatility is derived from the small data set.

Table 18. Model Accuracy Scores

Model	Training Accuracy	Testing Accuracy	RMSE	Rod Failure Prob Given Log Entry
k-Nearest Neighbors	0.8868	0.8549	0.3644	0.1736
Logistic regression	0.9114	0.8938	0.3044	0.2131
Gaussian Naïve Bayes	0.5034	0.4779	0.7172	0.2774
Bernoulli Naïve Bayes	0.9222	0.9266	0.2492	0.2228
Multinomial Naïve Bayes	0.9260	0.9096	0.2800	0.2285

The only model shown to be inaccurate was the Gaussian Naïve Bayes model, this is expected due to the simple fact that the Gaussian distribution is not the appropriate conjugate distribution to the data provided. The expected distribution is the Poisson-Gamma conjugate distributions and have different bounds. An important distinction is the close relationship the Bernoulli and multinomial distributions have to the gamma distribution, meaning that statistically these models hold great weight to being close to the expected result.

4.1.2 Problems Encountered

The greatest issue encountered with the machine learning models is the data size available. There were several issues with the data size used that required adjustments after the models predicted failures. The first one and most evident issue was the size of the dataset causing large uncertainties in the results, largely limits the effectiveness of using these data as for machine learning applications, and it limits the types of machine learning algorithms that should be considered and implemented. The next issue was the inherent bias encountered by these data. These data were taken from the corrective maintenance log which in turn causes the predictions to be conditioned towards failure of the components because these data comprise entirely of failures or other deficiencies.

4.1.3 Conditioning the results

The probabilities found initially may seem to be the raw probabilities of rod failure until the size of the data is considered. The data used are maintenance log entries presented to a regulatory body. The total number of entries are limited to maintenance occurrences, meaning that the resultant probability is an issue being fixed by maintenance. As a result, these conditions must be corrected with the equation below:

$$P(R) = \frac{P(R|M) \times P(M)}{P(M|R)} \tag{12}$$

Where P(R) is the probability that a rod drive issue occurs, P(R|M) is the probability that a rod drive issue occurs given that maintenance occurs, P(M) is the probability that maintenance will occur, and P(M|R) is the probability that maintenance occurs given a rod drive issue occurs.

4.1.4 Results and Validation

To produce a supervised machine learning model, the data was split and trained separately. Each model's mean, accuracy, and root mean squared was evaluated to determine the effectiveness.

The first expected result for the control rod drive failure rate was $1.54E-07$ from previous experiments consisting of 20 failures with $132{,}832{,}800$ demands of the control rod to operate [8]. The INL dataset is publicly available but the AGN-201m dataset is not, leading to the answer in Table 19. Table 19 is the expected answer through initial engineering judgement.

Table 19. Expected Answer from INL Failure Data [8]

Component	**Distribution**	**Mean**	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	**Error Factor**
Control Rod Fails to Operate	Gamma(α, β)	$1.54E-07$	20.50	$1.33E+08$	1.4

The Gamma distribution is a statistical conjugate to the Poisson distribution, which is derived from the time change of the binomial distribution. The Gamma distribution allows for certain model assumptions to drastically increase accuracy and viability of implementation. With the understanding that there is no reasonable way to achieve the mean rod drive failure probability due to the limited sample size and the sheer time difference, the probability can be recalculated by taking the total number of rod drive failures within the data and calculating a new gamma distribution. The new Gamma distribution was found to have parameters $\alpha = 26.5$ and $\beta = 3652.5\ days$ yielding a mean of $7.26E-03$.

Table 20 shows the tabulated calculations following the conditional probability formula. It highlights the results of all the variables from the above equation. Instances of the $P(M|R)$ and $P(M)$ are considered constant as a result of their independence to the dataframe. $P(M|R)$ is accepted to be 1 as all these data from the annual report are failures of some type. The value of $P(M)$ is accepted be a gamma distribution with parameters $\alpha = 119$ and $\beta = 3652.5\ days$.

Table 20. Model Conditional Probabilities

Model	$\boldsymbol{P(M\|R)}$	$\overline{\boldsymbol{P(R\|M)}}$	$\boldsymbol{P(M)}$	$\overline{\boldsymbol{P(R)}}$
k-Nearest Neighbors	1	0.1736	$3.26E-02$	$\mathbf{5.66E-03}$
Logistic regression	1	0.2131	$3.26E-02$	$\mathbf{6.95E-03}$
Gaussian Naïve Bayes	1	0.2774	$3.26E-02$	$\mathbf{9.04E-03}$
Bernoulli Naïve Bayes	1	0.2228	$3.26E-02$	$\mathbf{7.26E-03}$
Multinomial Naïve Bayes	1	0.2285	$3.26E-02$	$\mathbf{7.45E-03}$
Expected Gamma Distribution	N/A	N/A	N/A	$\mathbf{7.26E-03}$

4.1.4.1 Individual Components Results

For the individual components, the best performing modelling method was the expected Gamma distribution. The Gamma distribution was used to determine the motor fails to start, the leadscrew binding occurs, and the magnet failure probability. The model provided useful insight into the individual component failures used in SAPHIRE models. Table 21 shows the predicted failure rates for the current CRDM components including the motor failing to start, the magnets failing, or a leadscrew failing.

Table 21. Machine Learning Algorithms Predictions

Component	Predicted Failure Probability	Uncertainty
Motor fails to start	2.327E-03	4.122E-07
Magnet	1.505E-03	4.122E-07
Leadscrew	1.505E-03	6.371E-07

4.2 AGN-201m SAPHIRE 8 Reliability Model

4.2.1 Initiating Events

PRA is developed with a probability of an event happening that will cause a response from plant systems. These plant systems require a component or series of components to respond in a manner appropriate to mitigate or otherwise stop an undesired end. The event that initiates this chain is the initiating event. In PRA there are two types of initiating events that are investigated: internal and external events. These events occur in different ways but depending on various factors they can have different event trees and differing responses.

4.2.1.1 External Events

As is customary of PRA assessments, a discussion of fire, seismic, and severe weather PRA models were investigated and presented.

The general conclusion was that each of these external PRA events would follow identical fault trees for all credible initiating events due to the simplicity of the AGN-201m's mechanical and electrical configurations required for SCRAM bus functionality. In any external initiating event, the SCRAM bus is designed to cause the magnets to de-energize and the operator is tasked with turning off the AGN-201m console via depressing the power button or physically removing the power cord from the wall and promptly evacuating the facility. Thus, any further discretization of the model for external initiating events is moot and unnecessary.

4.2.1.2 Internal Events

Initiating events pertaining to the reactor facility were investigated as well. It was concluded that internal flooding and internal fire events were both not credible events and not significant in response difference from any other initiating event to warrant discretization from the general initiating event.

The most internal flooding that could occur in a quick and timely manner would be large breakage of the 990-to-1000-gallon shield tank around the core; this event has never occurred across any AGN-201 facility. Within the site boundaries there is no other form of internal water available in high volume. The next larges body of water inside the Lillibridge Engineering building is the 1000 Gallon tank in the Pocatello Pile – 1; this water source is in a separate room behind a separate set of security doors and as such is not credible for a large break leak to impact the AGN-201m reactor significantly.

Internal fire was also considered, and it was decided that the most probable source would be an electrical fire from adversarial action during a long period of poor maintenance of the console or other electrical equipment. There are preexisting security features accommodate for an internal fire and the reactor staff are currently adequately adept at maintenance thus the procedure for internal fire is identical to the event of external fire.

4.2.2 Constant Components

The model will be perturbed by the changing the CRDM from the original system measured with the failure probability. The components left constant will consist of the overall event tree, the console scram bus, the ventilation system, and lastly facility containment of fission products.

The model covers the CRDMs, operator participation within the reactor, and console components directly connected to or very closely associated with the reactor scram bus and rod drive mechanism. When making the initial event tree, the events discussed ended up falling into two categories for use: the reactor scram systems, and the reactor's penthouse emergency trip system. Figure 15 shows the two categories of events and their associated end states.

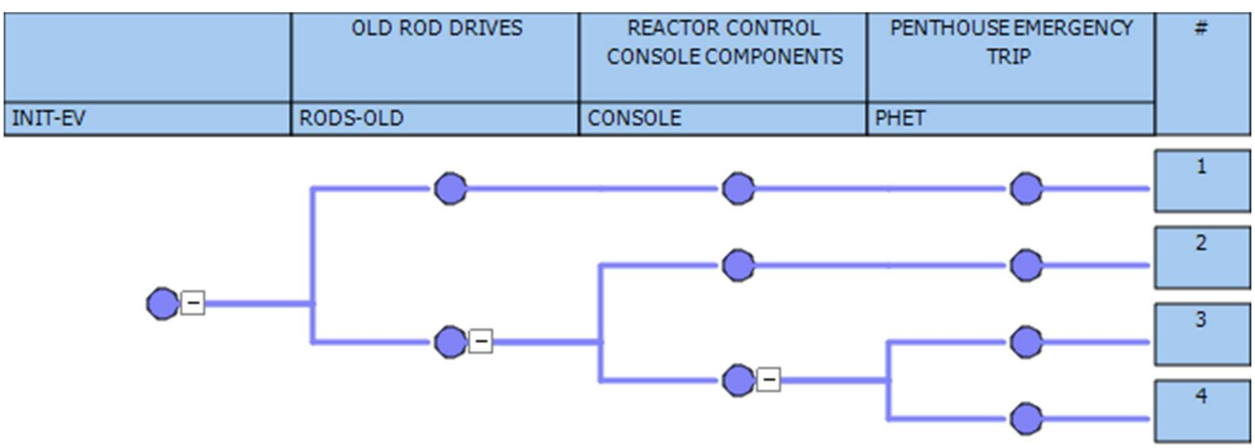

Figure 15. Event tree for ISU AGN-201m reactor.

On the top left of the image shows the initiating event for the event tree. Through investigation of the facility documentation, the overall procedure for any initiating event follows a single wholistic response sequence which can be surmised by the three-step process of ensuring the reactor scrams, ventilation does not allow for a release of nuclear or radiological material, and evacuate facility staff and civilians from the Lillibridge Engineering Building promptly. Steps beyond this are outside of the scope for PRA work and will not be discussed.

The reactor SCRAM system is designed to shut down the reactor immediately when one of the conditions in Table 1. These other methods are numerous and covered in Operating Procedure #1. All the SCRAM options are accounted for in the SCRAM BUS ensuring the AGN-201m is appropriately prepared to automatically or manually respond in the event of an emergency situation, or unanticipated reactivity increase.

For the first fault tree in the event tree is the scram event ‘CONSOLE’. The full fault tree can be seen in Figure 16. Each of the events shown at the top of the fault tree are associated with the electric power supply to the reactor. Due to the design of the AGN-201 reactor type, the reactor is fundamentally designed to exceed the shutdown margin of the reactor in the event of any power failure; these two events have been labelled ‘RXR-PWR-OFF’ and ‘FAC-PWR-LOSS’.

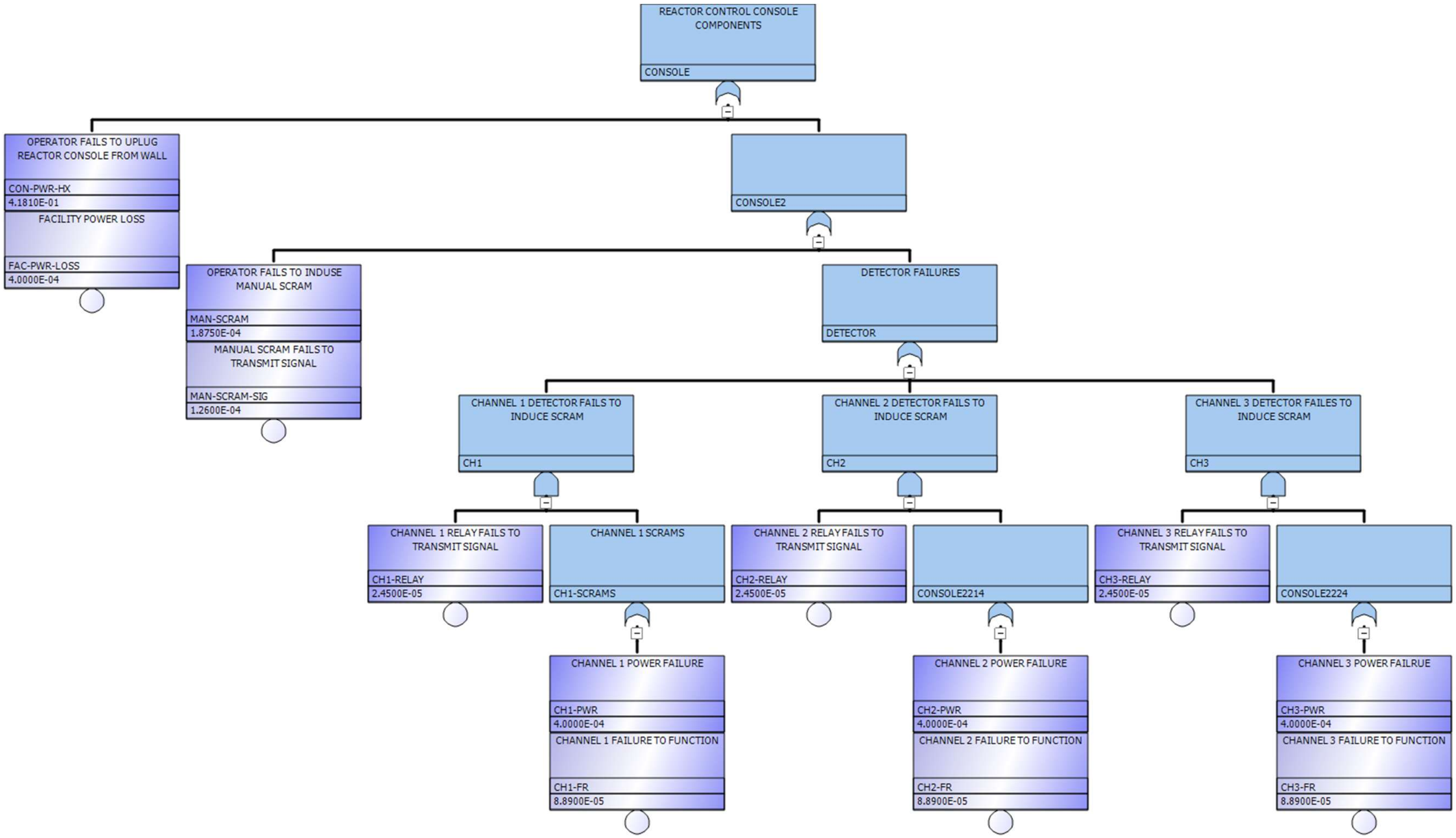

Figure 16. Reactor high level console fault tree.

The penthouse emergency trip fault tree in Figure 17 contains the data reported from the emergency drills performed annually, and as a result the components investigated are representative of an operator or observer's ability to perform a task. The task at hand is the ability to engage the penthouse emergency trip button within the NEL main hallway. As a result, with human factors quantification a series of questions follows in determining an appropriate probability of failure. Upon activation of the button the ventilation system can either deactivate or fail to deactivate, the probability of the penthouse ventilation system to deactivate with a successful human activation was determined to be 2.76E-03 and is expected to follow a beta distribution based on the components distribution in industry.

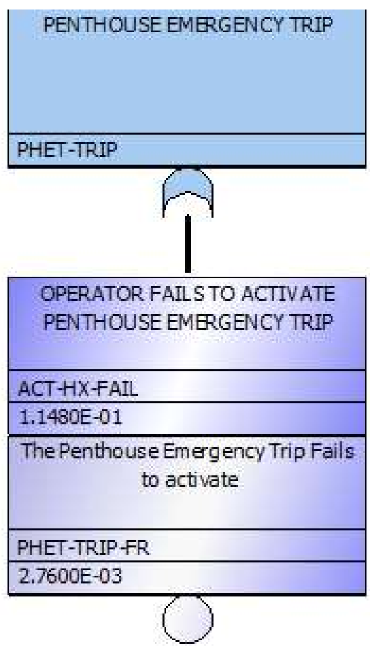

Figure 17. Penthouse emergency trip fault tree.

4.2.3 Model Using Original Design

Current facility documentation does not contain a risk assessment, as a result the data was compiled for all events from the past 10 years. The most concise document available containing failure data is the annual report submitted to the NRC. The annual report contains a date on which the event entry occurs, and a brief description of the cause and the processes made to correct or troubleshoot the issue. As the original CRDMs are all pre-built with only minor changes to limit switches, the best way to depict the failure probability was as a single integrated unit as that is what ISU received the rod drives as. A single rod drive can either fail to start motion, fail to stop motion, or fail to power off the magnets. The rod drive failure of interest used is the failure of the rod drive to power off the magnet and subsequently eject the rod drive using the spring eject, gravity assisted ejection system. Figure 18 shows the event tree for the current three CRDM configuration.

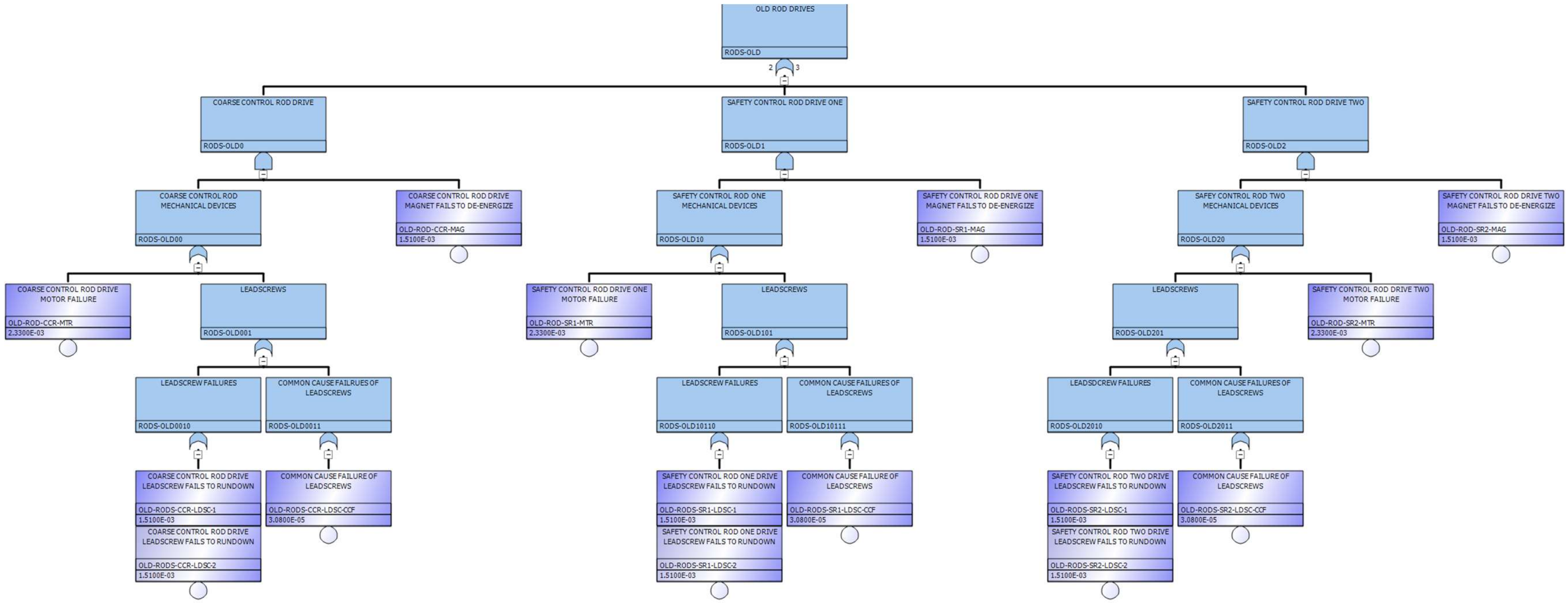

Figure 18. Fault tree for all three SCRAM-able current CRDM.

Constituent components accounted for by the integrated failure probability is the failure of the motor to operate on demand, failure of either leadscrew to operate, and failure of the magnet to disengage during a SCRAM event.

4.2.4 New Reactor Control Rod Drives

The new components are intended to perform identically to the currently installed design, one possible assumption was making predictions using machine learning predictions as the failure probability for all the new components. Some of the results found with the machine learning model were considered to be dubious and very uncertain so two qualitative approaches were also performed to provide an assessment of failure of the new components.

4.2.4.1 Fault Tree Analysis

As the parts from the new design have been purchased as individual components, it would make sense to develop a fault tree for rod failure, the components modelled within the fault tree were the new motor, new leadscrew, and the four new magnets. As seen in Figure 19, the logic within the fault tree was adjusted to account for the introduction of four new electromagnets and the removal of one of the leadscrews and the common cause failure of each magnet.

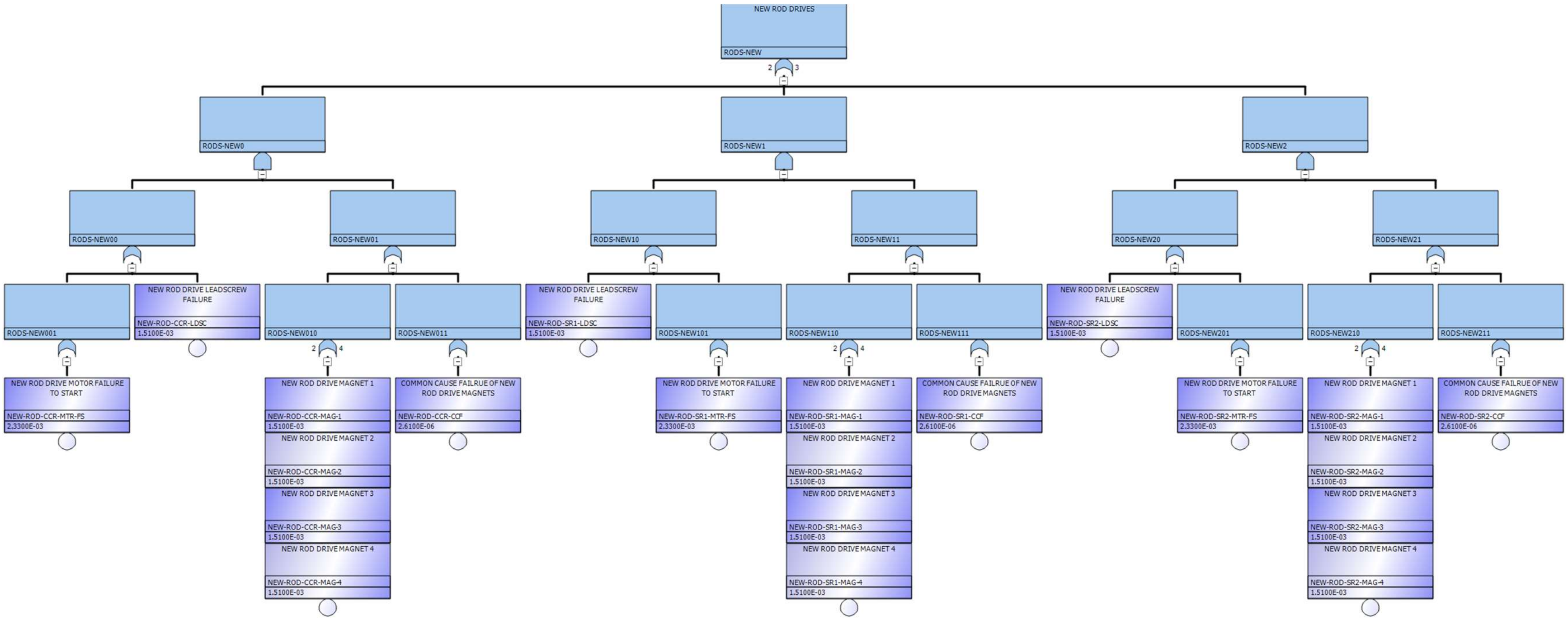

Figure 19. Fault tree for all three SCRAM-able new CRDM.

The assumed identicality highlights the logic changes made to the reactor in lieu of component reliability, which implies that the components should expectantly perform in a more conservative manner than what is determined in the PRA model. The new CRDM's fault tree is shown in Figure 20. One event of note that is new is the introduction of common cause failures of the magnet components, and the use of an if three out of four logic gate was determined from the expected weight from the forces of the spring and the force of gravity from the control rod and magnet plates respectively.

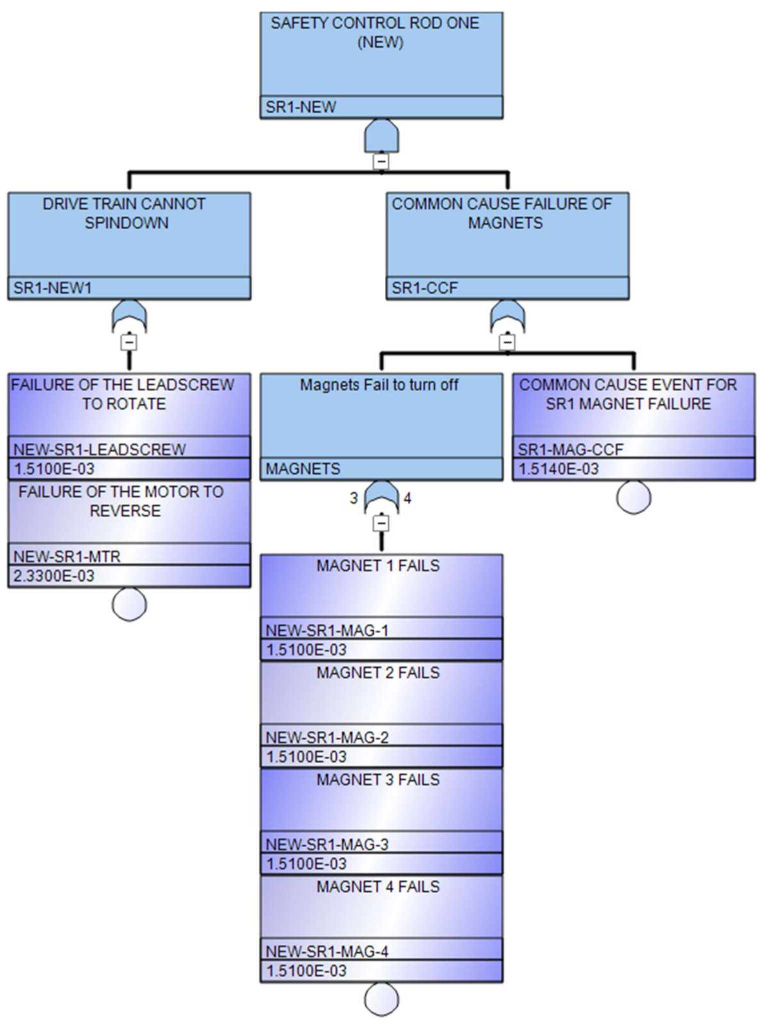

Figure 20. Fauilt tree of new components in safety control rod drive one.

4.2.5 Model Execution Configuration

The models were all run under the same settings to ensure minimal impact from differing settings. Table 22 and Table 23 depicts the settings used for all calculations within SAPHIRE. The truncation setting would be determined by starting with 1E-12 and decreasing an order of magnitude until the change in probability was less than 5%, a common practice in industry PRA. Due to the simplicity of the model and the facility, it was found that truncation as is done industry wide proved trivial; the time to solve all cutsets for all three trees was 0.349 seconds with no truncation for all three event trees.

Table 22. CRDM Event Tree Results and Settings

Event Tree Name	Probability (per demand)	Method	Number of Cutsets
NEW-RODS	1.361E-17	Min Cut Upper Bounds	23520
OLD-RODS-CLASSIC	2.296E-13	Min Cut Upper Bounds	1920

Table 23. CRDM Fault Tree Results and Settings

Fault Tree Names	Probability (per demand)	Method	Number of Cutsets
CONSOLE	4.185E-01	Min Cut Upper Bounds	10
PHET	1.054E-02	Min Cut Upper Bounds	3
RODS-NEW	1.170E-14	Min Cut Upper Bounds	588
RODS-OLD	1.980E-10	Min Cut Upper Bounds	48

4.2.5.1 Mean Time to Failure

To produce an average failure frequency for the AGN-201m reactor, the average number of demands annually, and the failure probability per demand are required to obtain the mean time to failure (MTTF). Using operational experience (OE) data from the AGN-201m for the years 2016 through 2020, a mean number of CRDM demands was found to be 160.2 demands per year. The following equation was used to determine the mean time to failure for each fault tree and event tree.

$$MTTF = Demands_{average} \times P(Failure) \tag{13}$$

Table 24 shows the average failure probability and mean time to failure found for the current CRDMs versus the new CRDMs expressed in failure per demand, average failure per year, and MTTF.

Table 24. CRDM Fault Tree and Event Tree Average Failure Frequency and MTTF

Event Tree and Fault Tree Name	Probability (per demand)	Average Failure Frequency (per year)	MTTF (years)
NEW-RODS	1.361E-17	2.18E-15	4.59E+14
OLD-RODS-CLASSIC	2.296E-13	3.68E-11	2.72E+10
RODS-NEW	1.170E-14	1.87E-12	5.34E+11
RODS-OLD	1.980E-10	3.17E-08	3.15E+07

4.2.6 Importance Measures of the Components

Fussell-Vesely, risk achievement worth, risk reduction, and Birnbaum sensitivity analyses were performed on both the new and the old models to determine the sensitivity of events in the current rod drive mechanisms. NUMARC 93-01 is the industry standard for the development of a PRA model in the nuclear industry. Within NUMARC 93-01 is the established the bounds of risk significant components via the utilization of Fussell-Vesely, risk reduction worth, and risk achievement worth and CDF contribution are required for an accurate determination of the risk significance to of each component.

4.2.6.1 Fussell-Vesely Importance Measure

The Fussell-Vesely importance measures the overall percent contribution of cutsets containing a particular basic event to the total risk from the model. The Fussell-Vesely importance measure is quantified in the equation below, where $F(i)$ is the risk from the cutsets containing said particular event and $F(x)$ subsequently is the total risk from the model.

$$FV_{xi} = \frac{F(i)}{F(x)} \tag{14}$$

4.2.6.2 Risk Achievement Worth Importance Measure

Risk achievement worth (RAW) importance measures the sensitivity of a single basic event by calculating the total risk in the event that an event's probability is 1, and has two calculated values associated with it, the risk increase ratio (RIR_{xi}) and the risk increase difference (RII_{xi}), as seen below.

$$RIR_{xi} = RAW_{xi} = \frac{F(1)}{F(x)} \tag{15}$$

4.2.6.3 Risk Reduction Importance Measure

The risk reduction importance (RRI) measure serves is the distance of guaranteeing a failure happens to the actual rate existing, measure of the risk change of not having a event $F(1)$, and can be calculated through the equation below.

$$RII_{xi} = RRI = F(1) - F(x) \tag{16}$$

4.2.6.4 Birnbaum Importance Measure

Birnbaum importance measures the rate of change in total risk due to a change the probability of an individual basic event and ranks events when they are altered from normal values.

$$Bi_x = \frac{\delta}{\delta x} F(x) \tag{17}$$

The Fussell-Vesely, RAW, Birnbaum importance measures for each model are shown in Appendix B Table 26 for the old CRDMs and Table 26 for the old CRDMs as single components.

4.2.6.5 Uncertainty Results

The uncertainty of the results for each fault tree was quantified using the build in Monte Carlo sampling. SAPHIRE is equipped with a sampling capability and plotting functions to produce probability densities and cumulative densities.

4.2.6.5.1 Current Rod Drives

The current CRDM's uncertainty was quantified, and the resulting uncertainty looks reminiscent of a Gamma distribution in shape. This is fitting for most basic events use a Gamma distribution for their uncertainty. Figure 21 shows the resulting probability distribution for the current CRDMs.

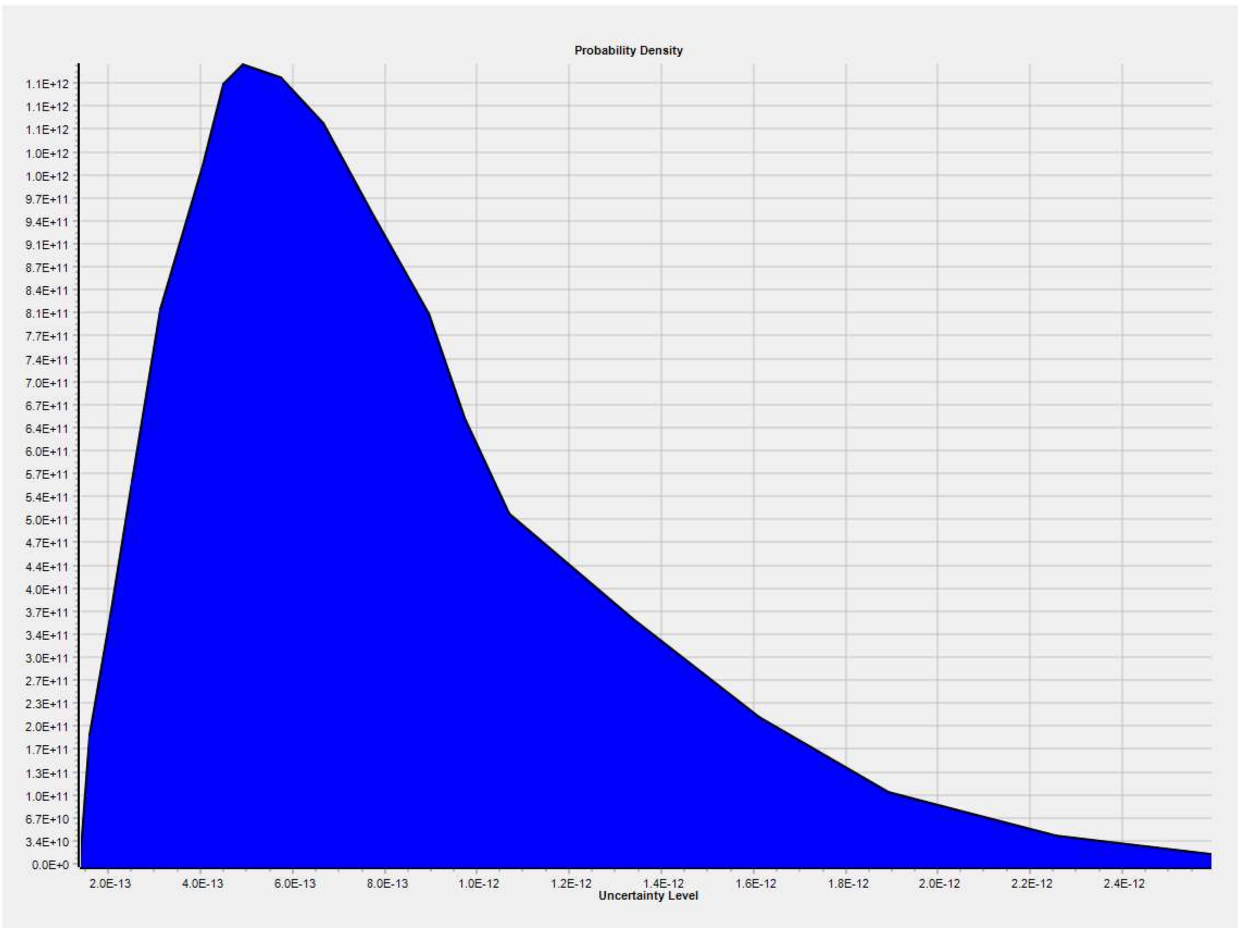

Figure 21. Probability density function of the current CRDM.

The current rod drive's probability density function was also quantified, resulting in Figure 22. It shows the sharp increase prior to the mean from Figure 21 and the plateauing of the distribution thereafter.

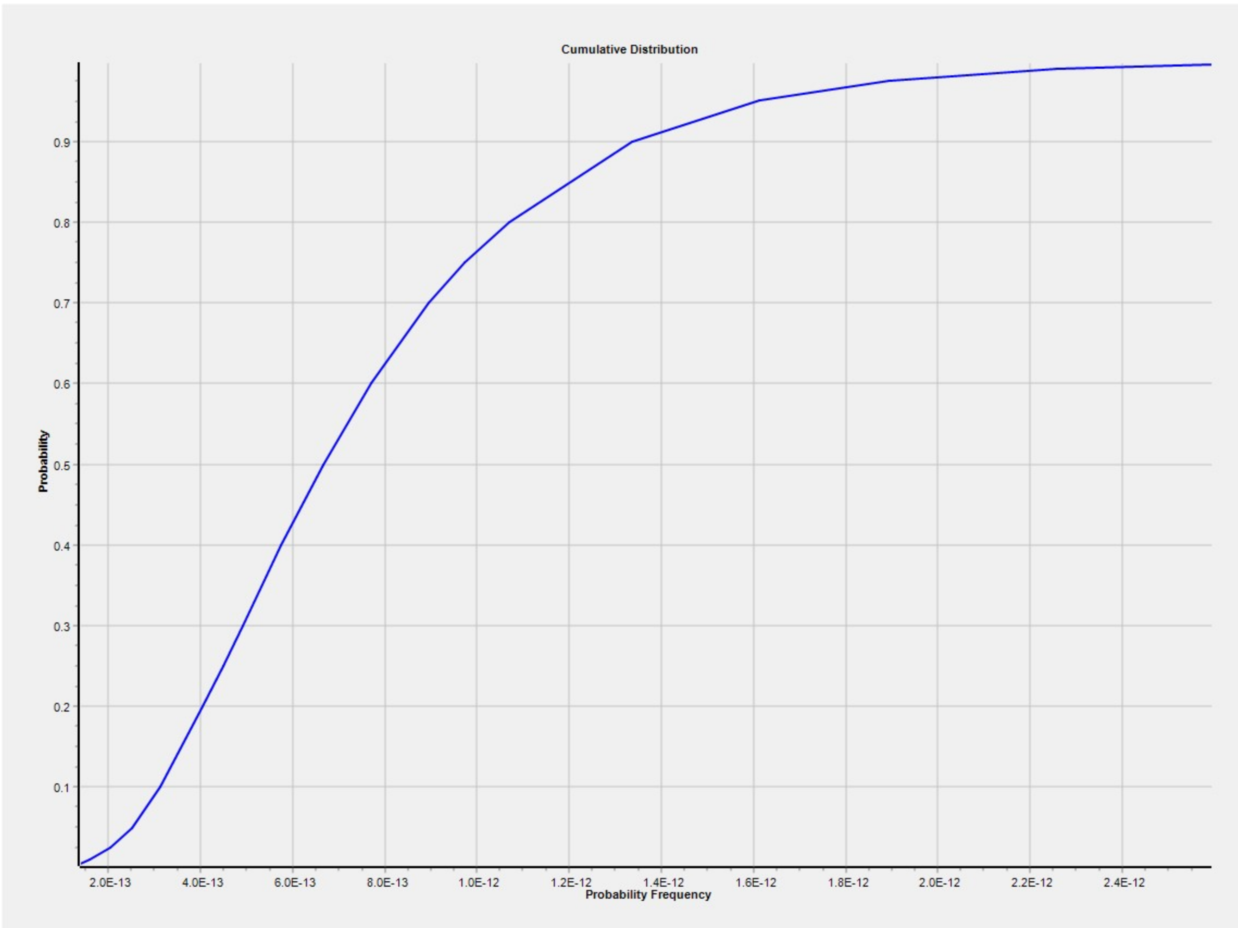

Figure 22. Cumulative density function of the old rod drives.

Table 25 shows the important parameters calculated from Monte Carlo sampling when creating the plots of Figure 21 and Figure 22. The maximum was calculated to be 4.106E-12 and the mean was found to be 7.767E-13. Table 25 shows that the sample size produced was found to be 10,000 with random seed 1677. The kurtosis implies that the resulting distribution is leptokurtic which is appropriate for a gamma distribution.

Table 25. Results of SAPHIRE Uncertainty Quantification for the New Rod Drives

Parameter	Value
Sample Size	10000
Random # Seed	1677
Events	34
Cutsets	1968
Point Estimate	7.722E-13
Mean Value	7.767E-13
5th % Value	2.538E-13
Median Value	6.781E-13
95th % Value	1.641E-12
Min Sample Value	5.629E-14
Max Sample Value	4.106E-12
Standard Deviation	4.503E-13
Skewness	1.542E+00
Kurtosis	6.833E+00

4.2.6.5.2 New Rod Drives

The approach to quantify the new CRDMs was to use the same basic event probabilities as the current CRDMs, assuming the new components are functionally identical to the current components. Despite the similar fault trees, it can be seen quantitatively that the new components are more reliable due to the inclusion of four cylinder magnets over one torus magnet. Using engineering judgement, it can be understood that the new components will perform better and have less probability of failure due to the lack of degradation and industry standard components instead of custom parts. Industry standard components will be available for a longer time than custom components and have higher quality assurance.

Chapter 5: Conclusions

The application of PRA practices in the nuclear industry combined with the application of machine learning has produced a rudimentary risk model for ISU's AGN-201m model. The results were shown to be very similar to the generic reliability parameters combined with the facility data used as a baseline for most commercial power plants in the United States. With respect to the new CRDM, it has been concluded through multiple qualitative analyses that it is equally reliable in design to the original design, but with the advantage of new reduced friction leadscrews and bearings, and new components all around that the immediate impact will result in reduced risk to a facility already of minimal risk at PRA levels 1, 2, and 3.

It was reasoned through a qualitative reliability analysis that the introduction of newer components that employ modern designs will improve the reliability, and that the implementation of newer technology is more likely to reduce undue failures of the reactivity manipulation required to remain at power. Despite the SCRAM functions not being at risk for the foreseeable future for the current rod drive design, the new rod drive design proved to reduce probability of loss of reactivity manipulation significantly. The reliability analysis with gamma distribution predictions yielded a result of 1.980E-10 (MTTF 3.15E+07) probability of failure of any two of the current CRDMs and 1.170E-14 (MTTF 5.34E+11) probability of failure of any two of the new CRDMs. The reliability analysis also yielded event tree solutions of 2.296E-13 (MTTF 2.72E+10) with the current CRDMs and 1.361E-17 (MTTF 4.59E+14) with the new CRDM design.

Chapter 6: Future Work

To complete the upgrade process, there are other steps that must be taken to ensure that the new control rod drive prototype can be used safely and preparing for the inevitable degradation and replacement in the unforeseeable future.

6.1 Code of Federal Regulations Part 10 Section 50.59 Evaluation

An initial 10 CFR 50.59 screening was presented to the reactor safety committee prior to performing any testing or investigation. The initial step of this investigation is the establishment of a risk model for the AGN-201m reactor independent of other reactor facilities. That step has come to fruition. Within Appendix B is the first and second 50.59 screening form covering the first screening of the desired change without formal evaluation. With the screening complete the next step is a more formal evaluation of each 50.59 screening question. Which was not completed within the scope of the reliability model development.

The initial prototype was machined constructed; however, with a physical prototype prototyping and testing will begin, and appropriate analysis for implementation can begin.

6.2 Material Analysis

The material selection comprises of brass, aluminum, and steel for the new CRDM design. It is known that brass is an alloy containing hazardous materials and when irradiated becomes mixed waste becoming a greater challenge to dispose of under current Environmental Protection Agency regulations. This does not pose a functional issue to implementation but does not prepare for end of life of the AGN-201m facility. The AGN-201m facility already has enough fuel, and materials to be able to operate for the next 200 years; meaning this preparation should not be considered as a major obstacle for implementation of the design change.

The current CRDM is constructed from brass meaning that the functional use of brass for large parts of the new design ismoot.

6.3 Model Refinement

The model's human reliability conclusions have been recommended to reactor training staff to further improve the human performance of operators but as these changes are under current implementation human performance values will be subject to change and expectedly decrease over time. SAPHIRE is limited to the implementation of SPAR-H human reliability which is one of numerous metrics that can be implemented for the use of human reliability estimation.

6.4 Data Acquisition for Machine Learning

The current risk models use a limited amount of data of maintenance log entries over the past 10 years that were documented within the annual report to predict a reasonable failure probability. The implementation of more data will produce more accurate results. It has been demonstrated that the application of machine learning for PRA based predictions is feasible, but the data utilized is insufficient for yielding results without high uncertainty.

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Appendix A: 10 CFR 50.59 Screening information

50.59 SCREEN

Number: ISU-50.59-2021-2 Page 1 of 2

Title: Reactor Control Rod Drive Upgrade

Description of Activity *(what is being changed and why):* **The reactor control rod drive upgrade is being changed to a single lead screw design from 2017 to allow for a lighter weight, more dependable, and overall safer design**

Safety Determination:

Does the proposed activity have the potential to affect nuclear safety or safe *facility* (I.e., Lillibridge Engineering Building) operation? ☐ YES ☒ NO

If this question is answered yes, do not continue with this procedure. Identify and report the concern to the Reactor Supervisor.

50.59 Screening Questions:

1. Does the proposed activity involve a change to an *SSC* that affects a design function described in the *FSAR*? ☐ YES ☒ NO
2. Does the proposed activity involve a change to a *procedure* that affects how the *FSAR* described *SSC* design functions are performed, controlled, or tested? ☐ YES ☒ NO
3. Does the proposed activity involve revising or replacing a *FSAR* described evaluation methodology that is used in establishing the *design bases* or used in *safety analyses*? ☐ YES ☒ NO
4. Does the proposed activity involve a *test or experiment not described in the FSAR,* where an *SSC* is utilized or controlled in a manner that is outside the reference bounds of the design for that *SSC* or is inconsistent with analyses or descriptions in the *FSAR*? ☒ YES ☐ NO
5. Does the proposed activity require a change to the ISU-AGN 201 Technical Specifications? ☐ YES ☒ NO

If all the screening questions are answered NO, then implement the activity per applicable approved *facility procedures(s)*. A License Amendment or a *50.59 Evaluation* is not required.

If Screen Questions 5 is answered YES, then request and receive a License Amendment prior to implementation of the activity.

If Screen Question 5 is answered NO but Question 1, 2, 3, or 4 is answered YES, then complete and attach a *50.59 Evaluation* form. [Refer to Attachment 9.2.]

NOTE: If the conclusion of the screening questions is that *50.59 Evaluation* is not required, provide justification for the "No" determination. In addition, list the documents (*FSAR,* Technical Specifications, and other Licensing Basis documents) reviewed where relevant information was found. Include section/page numbers. Use Page 2 of this form to document your statements.

	Print Name	Sign Name	Date
Preparer:	**Wesley Yockey**	W Yockey	2.17.21
Reviewer:	**Jonathan Scott**		
Reactor Supervisor:	**Dr. Mary Lou Dunzik-Gougar**		

AP-ISU-NEL-001, Revision 1
RSC Approval: January 1st, 2017 Attachment 9.1

50.59 SCREEN (Cont.)

Number: ISU-50.59-2021-2 Page 2 of 2

Title: Reactor Control Rod Drive Upgrade ____

If the conclusion of the five (5) Screening Questions is that a *50.59 Evaluation* is not required, provide justification to support this determination: *[Use and attach additional pages as necessary.]*

1. Does the proposed activity involve a change to an *SSC* that affects a design function described in the *FSAR*?

The proposed activity involves the complete changeover of all components within the control rod mechanism to newer or more reliable components. The FSAR only describes the use of a leadscrew, motor, chain, magnet, and bearing within the control rod drive mechanism. All these components are expected to function identically to or better than the current system. The synchro-generator will be replaced with a linear transducer allowing for more exact position indication and is expected to reduce chain binding issues associated with the current system.

2. Does the proposed activity involve a change to a *procedure* that affects how the *FSAR* described *SSC* design functions are performed, controlled, or tested?

The proposed activity would involve changing the position indication system of the reactor console to allow for the use of a linear transducer instead of an encoder. The change from the encoder to the linear transducer will cause the position indication system to function more accurately than the encoder system by providing exact position information instead of relative position information. The FSAR does not state that the position indication system is required to be a synchro generator.

3. Does the proposed activity involve revising or replacing a *FSAR* described evaluation methodology that is used in establishing the *design bases* or used in *safety analyses*?

The design basis of the control rod mechanism consists of the electromagnets and the spring driven gravity assisted ejection system. Which is being replaced by an identical system with newer and more reliable components to perform the exact same task described within the FSAR.

4. Does the proposed activity involve a *test or experiment not described in the FSAR,* where an *SSC* is utilized or controlled in a manner that is outside the reference bounds of the design for that *SSC* or is inconsistent with analyses or descriptions presented in the *FSAR*?

The rod drives have not been replaced before and as such a method of testing is not found within the FSAR. The new rod drive mechanism is aimed to be modelled and tested utilizing PRA concepts to prove the reliability and a model of the previous model will also be produced for simulations and testing to compare and ideally prove that the new system is safer and more reliable than the previous system.

List the document (*FSAR*, Technical Specifications, and other Licensing Basis documents) reviewed where relevant information was found. [Include section / page numbers.]
FSAR section 4.3 Page 54, FSAR Section 5.10 Page 105

Appendix B: Importance Measures

Table 26. Importance Measures of Current CRDM

Name	Count	Prob	FV	RIR	RRR	Birnbaum	RII	RRI	Uncertainty
CH1-FR	192	8.890E-05	0.000E+00	1.000E+00	1.000E+00	1.369E-17	1.369E-17	0.000E+00	3.045E-22
CH1-PWR	192	4.000E-04	0.000E+00	1.000E+00	1.000E+00	1.369E-17	1.369E-17	0.000E+00	0.000E+00
CH1-RELAY	384	2.450E-05	0.000E+00	1.001E+00	1.000E+00	2.637E-16	2.637E-16	0.000E+00	9.200E-21
CH2-FR	192	8.890E-05	0.000E+00	1.000E+00	1.000E+00	1.369E-17	1.369E-17	0.000E+00	3.045E-22
CH2-PWR	192	4.000E-04	0.000E+00	1.000E+00	1.000E+00	1.369E-17	1.369E-17	0.000E+00	0.000E+00
CH2-RELAY	384	2.450E-05	0.000E+00	1.001E+00	1.000E+00	2.637E-16	2.637E-16	0.000E+00	9.200E-21
CH3-FR	192	8.890E-05	0.000E+00	1.000E+00	1.000E+00	1.369E-17	1.369E-17	0.000E+00	3.045E-22
CH3-PWR	192	4.000E-04	0.000E+00	1.000E+00	1.000E+00	1.369E-17	1.369E-17	0.000E+00	0.000E+00
CH3-RELAY	384	2.450E-05	0.000E+00	1.001E+00	1.000E+00	2.637E-16	2.637E-16	0.000E+00	9.200E-21
CON-PWR-HX	192	4.181E-01	9.983E-01	2.389E+00	5.907E+02	5.483E-13	3.191E-13	2.292E-13	0.000E+00
FAC-PWR-LOSS	192	4.000E-04	9.497E-04	3.387E+00	1.001E+00	5.483E-13	5.481E-13	2.181E-16	0.000E+00
INIT-EV	1920	2.740E-03	1.000E+00	3.650E+02	1.900E+38	8.382E-11	8.359E-11	2.296E-13	0.000E+00
MAN-SCRAM	192	1.875E-04	4.490E-04	3.387E+00	1.000E+00	5.483E-13	5.482E-13	1.031E-16	0.000E+00
MAN-SCRAM-SIG	192	1.260E-04	2.941E-04	3.387E+00	1.000E+00	5.483E-13	5.482E-13	6.753E-17	9.781E-17
OLD-ROD-CCR-MAG	1280	1.510E-03	6.667E-01	4.419E+02	3.000E+00	1.014E-10	1.012E-10	1.531E-13	6.508E-14
OLD-ROD-CCR-MTR	320	2.330E-03	2.887E-01	1.246E+02	1.406E+00	2.845E-11	2.839E-11	6.629E-14	2.274E-14
OLD-ROD-SR1-MAG	1280	1.510E-03	6.667E-01	4.419E+02	3.000E+00	1.014E-10	1.012E-10	1.531E-13	6.508E-14
OLD-ROD-SR1-MTR	320	2.330E-03	2.887E-01	1.246E+02	1.406E+00	2.845E-11	2.839E-11	6.629E-14	2.274E-14

Name	Count	Prob	FV	RIR	RRR	Birnbaum	RII	RRI	Uncertainty
OLD-ROD-SR2-MAG	1280	1.510E-03	6.667E-01	4.419E+02	3.000E+00	1.014E-10	1.012E-10	1.531E-13	6.508E-14
OLD-ROD-SR2-MTR	320	2.330E-03	2.887E-01	1.246E+02	1.406E+00	2.845E-11	2.839E-11	6.629E-14	2.274E-14
OLD-RODS-CCR-LDSC-1	320	1.510E-03	1.871E-01	1.247E+02	1.230E+00	2.845E-11	2.841E-11	4.296E-14	1.832E-14
OLD-RODS-CCR-LDSC-2	320	1.510E-03	1.871E-01	1.247E+02	1.230E+00	2.845E-11	2.841E-11	4.296E-14	1.832E-14
OLD-RODS-CCR-LDSC-CCF	320	3.080E-05	3.809E-03	1.249E+02	1.004E+00	2.845E-11	2.845E-11	8.748E-16	2.429E-16
OLD-RODS-SR1-LDSC-1	320	1.510E-03	1.871E-01	1.247E+02	1.230E+00	2.845E-11	2.841E-11	4.296E-14	1.832E-14
OLD-RODS-SR1-LDSC-2	320	1.510E-03	1.871E-01	1.247E+02	1.230E+00	2.845E-11	2.841E-11	4.296E-14	1.832E-14
OLD-RODS-SR1-LDSC-CCF	320	3.080E-05	3.809E-03	1.249E+02	1.004E+00	2.845E-11	2.845E-11	8.748E-16	2.429E-16
OLD-RODS-SR2-LDSC-1	320	1.510E-03	1.871E-01	1.247E+02	1.230E+00	2.845E-11	2.841E-11	4.296E-14	1.832E-14
OLD-RODS-SR2-LDSC-2	320	1.510E-03	1.871E-01	1.247E+02	1.230E+00	2.845E-11	2.841E-11	4.296E-14	1.832E-14
OLD-RODS-SR2-LDSC-CCF	320	3.080E-05	3.809E-03	1.249E+02	1.004E+00	2.845E-11	2.845E-11	8.748E-16	2.429E-16
PHET-ACT-HX-FAIL	480	7.790E-03	7.697E-03	1.982E+00	1.008E+00	2.272E-13	2.255E-13	1.768E-15	0.000E+00
PHET-TRIP-FR	480	6.650E-06	0.000E+00	1.990E+00	1.000E+00	2.272E-13	2.272E-13	0.000E+00	2.135E-18
PHET-TRIP-FS	480	2.760E-03	2.722E-03	1.987E+00	1.003E+00	2.272E-13	2.266E-13	6.251E-16	9.158E-16

Table 27. Importance Measures of New CRDM

Name	Count	Prob	FV	RIR	RRR	Birnbaum	RII	RRI	Uncertainty
CH1-FR	2352	8.890E-05	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH1-PWR	2352	4.000E-04	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH1-RELAY	4704	2.450E-05	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH2-FR	2352	8.890E-05	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH2-PWR	2352	4.000E-04	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH2-RELAY	4704	2.450E-05	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH3-FR	2352	8.890E-05	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH3-PWR	2352	4.000E-04	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CH3-RELAY	4704	2.450E-05	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
CON-PWR-HX	2352	4.181E-01	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
FAC-PWR-LOSS	2352	4.000E-04	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
INIT-EV	23520	2.740E-03	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
MAN-SCRAM	2352	1.875E-04	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
MAN-SCRAM-SIG	2352	1.260E-04	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
NEW-ROD-CCR-CCF	2240	2.610E-06	1.900E+38	1.900E+38	1.900E+38	5.571E-13	5.571E-13	0.000E+00	3.016E-19

Name	Count	Prob	FV	RIR	RRR	Birnbaum	RII	RRI	Uncertainty
NEW-ROD-CCR-LDSC	7840	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.352E-15	2.352E-15	0.000E+00	1.515E-18
NEW-ROD-CCR-MAG-1	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-CCR-MAG-2	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-CCR-MAG-3	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-CCR-MAG-4	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-CCR-MTR-FS	7840	2.330E-03	1.900E+38	1.900E+38	1.900E+38	2.352E-15	2.352E-15	0.000E+00	1.880E-18
NEW-ROD-SR1-CCF	2240	2.610E-06	1.900E+38	1.900E+38	1.900E+38	5.571E-13	5.571E-13	0.000E+00	3.016E-19
NEW-ROD-SR1-LDSC	7840	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.352E-15	2.352E-15	0.000E+00	1.515E-18
NEW-ROD-SR1-MAG-1	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-SR1-MAG-2	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-SR1-MAG-3	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18

Name	Count	Prob	FV	RIR	RRR	Birnbaum	RII	RRI	Uncertainty
NEW-ROD-SR1-MAG-4	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-SR1-MTR-FS	7840	2.330E-03	1.900E+38	1.900E+38	1.900E+38	2.352E-15	2.352E-15	0.000E+00	1.880E-18
NEW-ROD-SR2-CCF	2240	2.610E-06	1.900E+38	1.900E+38	1.900E+38	5.571E-13	5.571E-13	0.000E+00	3.016E-19
NEW-ROD-SR2-LDSC	7840	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.352E-15	2.352E-15	0.000E+00	1.515E-18
NEW-ROD-SR2-MAG-1	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-SR2-MAG-2	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-SR2-MAG-3	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-SR2-MAG-4	6720	1.510E-03	1.900E+38	1.900E+38	1.900E+38	2.515E-15	2.515E-15	0.000E+00	1.614E-18
NEW-ROD-SR2-MTR-FS	7840	2.330E-03	1.900E+38	1.900E+38	1.900E+38	2.352E-15	2.352E-15	0.000E+00	1.880E-18
PHET-ACT-HX-FAIL	5880	7.790E-03	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00
PHET-TRIP-FR	5880	6.650E-06	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00

Name	Count	Prob	FV	RIR	RRR	Birnbaum	RII	RRI	Uncertainty
PHET-TRIP-FS	5880	2.760E-03	1.900E+38	1.900E+38	1.900E+38	0.000E+00	0.000E+00	0.000E+00	0.000E+00

Appendix C: Literature Review

6.4.1 Senior Design Group Rod Drive Design

Citation:

M. W. Beatty, B. A. Fehringer, D. E. Axelson, J. R. Harding and M. J. Daniels, "ISU AGN-201M Reactor Control Rod Drive Redesign," Idaho State University, Pocatello, 2018.

- Origins:

  The Control Rod Redesign document was prepared with collaboration between the senior design group, lead a former senior reactor operator, and the former reactor supervisor in order to address the approaching obsolescence with the rod drive mechanisms within the AGN-201m.

- Purpose:

  The senior design project that covers the physical design employed within the rod redesign process. The document covers the feasibility of the project and largely shows the physical possibility of implementing the new design.

- Value:

  The Control Rod Redesign document exhibits the design being evaluated in this thesis. Part of what was done for the senior design is testing the material and general physics of a single leadscrew design, some of those tests will provide reliability data that will be used for a changeover comparison and lifetime investigation.

- Limitations:

  As is with many senior design projects, there is a notable consideration as to the accuracy of certain aspects. Certain claims must be scrutinized to ensure the rod drive will function as intended with the lifespan intended.

6.4.2 Nuclear Energy University Program Grant

Citation:

A. Ali, "A New Control Rod Drive Mechanism Design for the ISU AGN-201M Reactor," Nuclear Energy Univerisy Program, 2020.

- Origins:

  The old rod drive design uses a double leadscrew mechanism, is made of steel making it heavy, and can be upgraded using different components. Dr. Amir Ali applied for the Nuclear Energy University Program (NEUP) grant to pay for the upgrade and initiate the redesign and implementation of the new rod drive mechanism.

- Purpose:

  The grant is paying for the prototyping and development of the new control rod drive mechanisms. The grant covers the selected design from the senior design project covering the same goal. Taking the best design and aiming to implement it.

- Value:

  The grant funded the machining and purchasing of new components crucial to the new rod drive mechanism's design and provided attainable goals with respect to publications and annual technical memos and a final report.

- Limitations:

  Although the grant lays out a design consideration and goal, the grant does not include methodology on the probabilistic risk assessment side of the project.

6.4.3 Idaho State University – Technical Specifications

Citation:

Idaho State University AGN-201m Research Reactor, "Technical Specifications," Idaho State University, Pocatello, 2011.

- Origins:

  The technical specifications document is one of the licensing documents for the AGN-201m reactor at Idaho State University which has been amended over the years, the most recent being 2011.

- Purpose:

  The purpose of the technical specifications provides is to provide limitations of the facility. These limitations impose design constraints on any changes that can be considered in addition to any changes in the administrative hierarchy.

- Value:

  The technical specifications provide a technical description of reactor systems, lists off many definitions, and provides administrative controls. This document provides important timeframes for the AGN-201m in question.

- Limitations:

  Some information within the technical specifications provides specific information to the makeup of the reactor. Specific information will be generalized unless required for risk-modelling purposes.

6.4.4 Idaho State University – Safety Analysis Report

Citation:

Idaho State University AGN-201m Research Reactor, "Safey Analysis Report," Idaho State University, Pocatello, 2021.

- Origins:

  The Safety Analysis Report (SAR) is one of the licensing documents for the AGN-201m Reactor at Idaho State University. The SAR was amended in 2021 following the control console upgrade in 2021.

- Purpose:

  The purpose of the SAR is to provide a wholistic analysis of the facility using qualitative of quantitative analysis. The report describes the general location, design, and characteristics of the AGN-201m at Idaho State University. The safety analysis portion of the document highlights the reactivity considerations, shielding evaluations, and design basis accidents such as loss of water shielding and tornadoes.

- Value:

  The SAR provides prior safety analysis data, including natural phenomena and the general design information of the current rod drive systems.

- Limitations:

  The SAR does not explicitly provide limitations, but is an analysis describing the current reactor system, and does not account for a new design.

6.4.5 Prior Publication about the Control Rod Drive Mechanism

Citation:

W. Yockey, A. Ali and C. Pope, "Development of a new control rod drive mechanism design for the ISU AGN-201M reactor," Annals of Nuclear Energy, 2022.

- Origins:

  Following the initiation of the rod drive upgrade project, a publication was underway on the specific design and development of the new rod drive mechanism versus the old rod drive mechanism.

- Purpose:

  To produce a concrete and public idea of the design work of this project, the paper covers the differences in the two rod drive designs and the proposed benefits of the new design in a comprehensive manner. A discussion on the potential weight reduction, newer materials and methodologies, and easier maintenance is addressed within this paper to encapsulate the engineering benefits of the new design and its application.

- Value:

  The paper discusses the design aspect of the project and formally discusses the senior design group's contributions to the project, and the idea of using probabilistic risk assessment to benchmark the new design.

- Limitations:

  The paper does not address in depth the probabilistic models developed in this project to benchmark the effectiveness of the design.

6.4.6 United States Nuclear Regulatory Commission – Fault tree Handbook

Citation:

W. E. Vesely, F. F. Goldberg, N. H. Roberts and D. F. Haasl, "NUREG-0492: Fault Tree Handbook," United States Nuclear Regulatory Commission, Washington DC, 1981.

- Origins:

  The fault tree handbook comes from a course entitled “System Safety and Reliability Analysis” in 1975 acting as a risk assessment training program sponsored by the Probabilistic Analysis Staff.

- Purpose:

  The handbook was developed to serve for the course but to also make it available to others as at the time the concepts of fault tree development was barren and vacant of documentation.

- Value:

  While the handbook is a very old document, the document has not changed over this time and the overall processes discussed in this document are not disputed, and still employed by regulators. This fault tree handbook overall streamlines the fault tree generation process and provides helpful insights on the function and requirements of SAPHIRE 8 and CAFTA 6 and their application.

- Limitations:

  With the Insights section there are some nuances with the ISU AGN-201m Reactor that are of course not discussed and will require justification for approval through the appropriate administrative personnel.

6.4.7 SAPHIRE Basics

Citation:

C. Smith, J. Knudsen, M. Calley, S. Beck, K. Kvarfordt, and T. Wood, "SAPHIRE basics: an introduction to probabilistic risk assessment via Systems Analysis Program for Hands-on Integrated Reliability Evaluations (SAPHIRE) software", Idaho National Laboratory, Idaho Falls, 2009.

- Origins:

  SAPHIRE, originally known as IRRAS was originally released in 1987 to assist in probabilistic risk assessment (PRA). In 1997, IRRAS was renamed SAPHIRE and included more features and reduced runtime.

- Purpose:

  SAPHIRE is a PRA software which is used in fault tree and event tree creation, cut set generation and quantification, importances measurement, external event analysis, and common cause failure event generation. The SAPHIRE basics manual examines the application and validity of PRA and the use of SAPHIRE within PRA.

- Value:

The manual was useful in determining how to produce certain models and quantify the quality of the models and produce comprehensive results.

- Limitations:

  The SAPHIRE manual does not give information involving troubleshooting the software, determining the value of a model, or guidance beyond SAPHIRE usage.

6.4.8 Nuclear Regulatory Commission – Title 10 Code of Federal Regulations

Citation:

Nuclear Regulatory Commission, "NRC Regulations Title 10, Code of Federal Regulations," Nuclear Regulatory Commission, 2015. [Online]. Available: http://www.nrc.gov/reading-rm/doc-collections/cfr/.

- Origins:

  Title 10 of the Code of Federal Regulations (10 CFR) is the set of rules in which the Nuclear Regulatory Commission (NRC) withhold following the Energy Reorganization Act of 1974, where the NRC replaced all licensing and regulatory functions of the Atomic Energy Commission.

- Purpose:

  The 10 CFR's provide all the rules and regulations that a facility will need to meet to operate with nuclear material in a safe, secure, and legal manner. The site is available to all facilities with up-to-date information on said rules.

- Value:

  The AGN-201m at ISU is subject to meeting the 10 CFR rules to keep personnel safe, informed and competent, and to continue operation of various facilities on campus including but not limited to the reactor, subcritical assembly, and particle accelerator.

- Limitations:

  The site provides the criteria to meet for the facility license but does not provide the methods that ISU utilizes to meet said legal requirements. This site will however provide guidance on the processes involved with testing and proving the improved safety mechanisms involved with the new CRDMs

6.4.9 Idaho State University – Annual reports

Citation:

Idaho State University Nuclear Engineering Department, "Annual Reports 2010-2020," Idaho State University, Pocatello, 2010-2020.

- Origins:

  As laid out in 10 CFR 50, ISU is required annually to submit an annual report ot the NRC covering fuel burnup in the year, dose assessments for reactor personnel, among other important operations information.

- Purpose:

  The annual reports document covers the reactors maintenance, Dose Assessment, and fuel burnup, and works to ensure that the facility is operating within the technical specifications.

- Value:

  The ten-year period described within the document represents the most recent maintenance procedures within the facility and shall cover any rod drive issues associated with the current rod drive design. The data will prove valuable to generating a frequency function, probability density function and estimate a single failure rate for the reactor's various rod drive components.

- Limitations:

  The document covers the maintenance log's entries, which are written by various operator technicians and are not always obviously clear on the verbiage used to describe an issue. As a result, machine learning algorithms will prove useful in developing a tally, and quantification system of failure rates over a time frame.

6.4.10 Idaho State University – Emergency Drills

Citation:

Idaho State University Nuclear Engineering Department, "AGN-201m Emergency Drills," Idaho State University, Pocatello, 2010-2021.

- Origins:

  As laid out in 10 CFR 50, ISU is required annually to perform an emergency drill to assess the reliability of operators and local emergency services on the performance of handling any reasonable emergency that can happen at the ISU AGN-201m reactor.

- Purpose:

  The document aptly documents the drills and emergency services of reacting to reactor upsets and ensures that operators can follow through with emergency operations when called upon.

- Value:

  The document houses valuable human capability information for the reliability model. This document will also possess criticism of systems within the AGN-201m and assess some initiating events that are reasonable for the facility to experience in its lifetime.

- Limitations:

  The emergency drill data will not be useful in the current form and will need to be analyzed to convert it into reasonable failure rates that can further be developed into an appropriate probability density function model or single failure probability.

6.4.11 Handbook of Human Reliability Analysis

Citation:

A. Swain and H. Guttmann, “Handbook of human reliability analysis with emphasis on nuclear power plant applications”, Sandia National Laboratories, Albequerque, 1985.

- Origins:

  Following the implementation of probabilistic risk assessment (PRA) in the nuclear industry, a method of quantifying human reliability was the next area of improvement. An initial draft of the Handbook of Human Reliability Analysis was circulated around the PRA and human reliability analysis (HRA) industry experts as a means of creating an agreeable and comprehensive method to standardize HRA. Given the intial draft’s comments, the handbook implemented the industry experts' recommendations to create a general guide to HRA.

- Purpose:

  The Handbook of Human Reliability Analysis was produced to incorporate HRA into PRA in order to produce a holistic model of nuclear facilities. The book introduces basic concepts of PRA and HRA, technical terms in the fields of HRA and PRA, and models for human performance.

- Value:

  The handbook is a comprehensive guide to the implementation of HRA including models and methodology behind human performance at a nuclear facility. The handbook provided an overall idea of the interactions between humans and machines using human machine interfaces (HMI) such as the AGN-201m control console, chart recorder, and wall area monitor.

- Limitations:

  Due to the handbook being for facilities of a larger size than the AGN-201m and with more complicated controls, the general models did not conform to the AGN-201m without modification.

6.4.12 Idaho State University AGN-201m – Console Changeover Information

Citation:

D. Montenegro and J. Bennion, “New Control Console for the Idaho State University’s AGN-201 Nuclear Reactor”, Innovations in Nuclear Engineering Education, Training, and Distance Learning, Idaho Falls, 2009.

- Origins:

  Due to the obsolescence of 1950’s components being used in the AGN-201m control console, ISU underwent a project to update old components to more modern solid-state electronics, including the control console.

- Purpose:

  To reduce the dependence on custom circuitry and vacuum tubes, the authors of this document designed a new control console to improve processing capacity while within technical specification limits.

- Value:

  The New Control Console paper describes in discretized sections the original design of the “new control console” and portions of the reactor protection system being updated, including the control rod magnets, scram and interlock buses, and neutron channels.

- Limitations:

  The document does not explicitly provide any data useful in risk analysis and is more of a proposal than a research paper, yielding no results of the final design.

6.4.13 Idaho State University-- SCRAM, Interlock and Magnet Improvements

Citation:

A. Mallicoat and C. Pope "Design improvements to the ISU AGN-201 reactor SCRAM, interlock, and magnet circuits", Annals of Nuclear Energy, Vol. 136, 2020.

- Origins:

  The original design of the ISU AGN-201 reactor involves 1950's vacuum tube technology and custom circuit boards. To compensate for the obsolescence, ISU has created a new console project to upgrade components to modern standards.

- Purpose:

  The proposed design improvements include rebuilding the AGN-201 safety circuit to include standard solid-state electronics and upgraded magnets to ensure the SCRAM, interlock, and magnet circuits are easily serviceable and repairable in modern times.

- Value:

  The document allows for inferred reliability metrics and highlighting the new design and components in the new SCRAM, interlock and magnet systems.

- Limitations:

  The paper does not discuss reliability in a probabilistic risk assessment manner, only implying the risk is negligible with the proposed changes.

6.4.14 Idaho National Laboratory Light Water Reactor Sustainability Program- Risk Assessment

Citation:

H. Bao, H. Zhang, and K. Thomas, "An Integrated Risk Assessment Process for Digital Instrumentation and Control Upgrades of Nuclear Power Plants", Idaho National Laboratory, Idaho Falls, 2019.

- Origins:

  The light water reactor sustainability program was designed to research and develop tools and methodologies to allow for the continued safe operation of current commercial nuclear power plants. "An Integrated Risk Assessment Process for Digital Instrumentation and Control Upgrades of Nuclear Power Plants" addresses the necessity for an accurate risk evaluation of software and hardware upgrades as the commercial fleet moves to more advanced technology to continue to operate.

- Purpose:

  As analog systems age and light water reactors move towards the use of digital systems involving the operation and maintenance of the reactor, a comprehensive process was developed to accurately assess risks to factor software and digital component risks through common cause failure analysis and plant transient responses.

- Value:

  A portion of "An Integrated Risk Assessment Process for Digital Instrumentation and Control Upgrades of Nuclear Power Plants" includes a discussion on human reliability assessment including common cause failure estimates for unsafe control actions.

- Limitations:

  A majority of the document considers digital instrumentation and control upgrades in conjunction with cybersecurity concerns and software failures. Due to the simplicity and lack of software in the proposed control rod upgrade, limitations exist on assessments of cybersecurity and software failures.

6.4.15 NUREG/CR-6928

Citation:

Z. Ma, T. Wierman, and K. Kvarfordt, "Industry-average performance for components and initiating events at U.S. commercial nuclear power plants", Idaho National Laboratory, Idaho Falls, 2021.

- Origins:

  The United States Nuclear Regulatory Commission (NRC) produces a set of risk models known as the Standardized Plant Analysis Risk (SPAR) models to provide the NRC assistance in the Significant Determination Process and confirm licensee risk analysis during license amendments. Originally, SPAR models were produced using industry performance and data sets acquired in the NURGEG-1150 studies (published in 1990).

- Purpose:

  Every few years SPAR models are updated to reflect current industry performance. NUREG/CR-6928 contains a comprehensive list of basic events from SPAR models, including distinctions between alternating/running component events, failure to run events (within the first hour), and failure to continue run events (beyond the first hour). NUREG/CR-6928 contains industry performance averages for unreliability in components, unavailabilities of parallel systems, special event probabilities, and initiating events.

- Value:

  NUREG/CR-6928 provides an estimate for component failure rates in industry standard components such as relays and switches. SPAR-H (Human reliability) is used for quantification of human events.

- Limitations:

  The SPAR models and use of NUREG/CR-6928 fall apart with specific components not listed, such as radiation detection measurement failure rates and non-standard components such as the AGN-201's motors.

6.4.16 AGN-201K PRA Analysis

Citation:

I. Ahmed, E. Zio, and G. Heo, "Risk-informed approach to the safety improvement of the reactor protection system of the AGN-201K research reactor", Kyung Hee University, Suwon, 2019.

- Origins:

  Following the Fukushima accident in 2011, Korea has required all nuclear power plants to conduct periodic safety reviews including probabilistic risk assessments (PRA). Despite periodic safety reviews being conducted for power plants, research reactors are not required to conduct a periodic safety review.

- Purpose:

Researchers at Kyung Hee University determined conducting a risk assessment for the AGN-201K reactor protection system to be a valuable endeavor. Through incorporating probabilistic risk assessment (PRA) importance measures and sensitivity and uncertainty analysis, the models produced provides potential safety improvements ranked on their importance to facilitate the upgrade process.

- Value:

The AGN-201K reactor protection system PRA provides data previously unavailable to the AGN-201m facility at ISU including neutron instrumentation channel failure rates and human reliability analysis from an AGN-201.

- Limitations:

The AGN-201K risk assessment includes the original un-upgraded reactor protection system including vacuum tube systems and AGN-201K specific data. The aim of the risk assessment is to assess the risk of failure of the reactor protection system, not CRDMs.

6.4.17 Guidelines for Hazard Evaluation Procedures

Citation:

S. S. Grossel, Guidelines for Hazard Evaluation Procedures, Center for Chemical Process Society, 2008.

- Origins:

The Center for Chemical Process Safety (CCPS) originally published the Guidelines for Hazard Evaluation Procedures in 1985 to disseminate hazards and risks associated with chemical plant safety. The CCPS updates the text to include new findings and hazards analysis methods to ensure safety with chemical processes.

- Purpose:

  The Guidelines for Hazard Evaluation Procedures provides a framework to conduct hazard evaluations and how the framework can be applied through multiple methodologies, such as failure modes and effects analysis (FMEA) or fault tree analysis.

- Value:

  The text is used across industries to conduct hazard evaluation procedures such as FMEA and helped with evaluating the effectiveness of solutions presented in this thesis.

- Limitations:

  Due to the broad scope of the document, specific nuclear hazards such as detector ruptures were not covered in the text.

Appendix D: Python Reliability Development Script

```
…
# Importing all things needed EXCEPT MODELS
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from collections import defaultdict
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import statsmodels.api as sm
import seaborn as sb
import math

# This data is not used but is a demonstrative of what I started with
DataInitial = pd.read_csv('https://gitlab.com/WickedWess/cs-final-rod-drive-risk/-
/raw/main/Decade_Compilation2010-2020.csv')
DataInitial.head()

# This will start by importing the new dataset having compiled what the description means with a set of
boolean and single string statements.
DataFull = pd.read_csv('https://gitlab.com/WickedWess/cs-final-rod-drive-risk/-
/raw/main/Decade_Compilation2010-2020NEW.csv')
DataFull.head(5)

DataFull["Solution"].unique()
DataFull.head()

# Start with Cleaning up the Data from som typos / empty entries
DataFull = DataFull.drop(columns=["Unnamed: 15", "Unnamed: 16", "Unnamed: 17", "Unnamed: 18"])
DataFull = DataFull.dropna()
DataFull.loc[DataFull["Solution"] == "replacement","Solution"] = "Replacement"
DataFull.loc[DataFull["Solution"] == "repair","Solution"] = "Repair"
DataFull.loc[DataFull["Solution"] == "recalibration","Solution"] = "Recalibration"
# due to the excessively small data set here I will merge rebuild with modifications as they are close
enough
DataFull.loc[DataFull["Solution"] == "rebuild","Solution"] = "Rebuild"
DataFull.loc[DataFull["Solution"] == "Modification","Solution"] = "Rebuild"
```

```
# Maintenance is not a failure so we will replace maintenance as None
DataFull.loc[DataFull["Solution"] == "Maintenance", "Solution"] = "None"
DataFull.loc[DataFull["Solution"] == "none","Solution"] = "None"
DataFull["Solution"].unique()

DataFull['Description'].str.len().plot.hist()
DataFull = DataFull.drop('Date Performed',axis=1)
DataFull = DataFull.drop('Description',axis=1)
DataFull = DataFull.drop('Console New OR Old',axis=1)
DataFull = DataFull.drop('Solution',axis=1)


DataFull[['Rod Drive Failure','Motor Failure','Magnet Failure','Leadscrew Failure','potentiometer
failure','Microswitch Failure','Console failure','Detector Failure','Channel 1 Failure','Channel 2
Failure','Channel 3 Failure']] *= 1
DataFull.head()

# I will replace the Data Frame above with a more useable form I made on my GitLab.
# Due to the small size and the inability of a computer to comprehend language in a neuanced manner many of
the booleans must be added manually.
DataFull['Console Total Failures'] = 0
DataFull['Rod Drive Total Failures'] = 0
DataFull['Motor Total Failures'] = 0
DataFull['Magnet Total Failures'] = 0
DataFull['Microswitch Total Failures'] = 0
DataFull['Potentiometer Total Failures'] = 0
DataFull['Detector Total Failures'] = 0
DataFull['Channel 1 Total Failures'] = 0
DataFull['Channel 2 Total Failures'] = 0
DataFull['Channel 3 Total Failures'] = 0
DataFull['Leadscrew Total Failures'] = 0
RodFailLast = defaultdict(int)
MotorFailLast = defaultdict(int)
LeadscrewFailLast = defaultdict(int)
PotFailLast = defaultdict(int)
MicFailLast = defaultdict(int)
MagFailLast = defaultdict(int)
ConFailLast = defaultdict(int)
DetFailLast = defaultdict(int)
Ch1FailLast = defaultdict(int)
```

```
Ch2FailLast = defaultdict(int)
Ch3FailLast = defaultdict(int)

for index, row in DataFull.iterrows():
  FailureRod = row['Rod Drive Failure']
  DataFull.loc[index,'Rod Drive Total Failures'] = RodFailLast[FailureRod]
  RodFailLast[FailureRod] += int(row['Rod Drive Failure'])
  FailureMotor = row['Motor Failure']
  DataFull.loc[index,'Motor Total Failures'] = MotorFailLast[FailureMotor]
  MotorFailLast[FailureMotor] += int(row['Motor Failure'])
  FailureLeadscrew = row['Leadscrew Failure']
  DataFull.loc[index,'Leadscrew Total Failures'] = LeadscrewFailLast[FailureLeadscrew]
  RodFailLast[FailureRod] += int(row['Rod Drive Failure'])
  FailurePot = row['potentiometer failure']
  DataFull.loc[index,'Potentiometer Total Failures'] = PotFailLast[FailurePot]
  PotFailLast[FailurePot] += int(row['potentiometer failure'])
  FailureMic = row['Microswitch Failure']
  DataFull.loc[index,'Microswitch Total Failures'] = MicFailLast[FailureMic]
  MicFailLast[FailureMic] += int(row['Microswitch Failure'])
  FailureMag = row['Magnet Failure']
  DataFull.loc[index,'Magnet Total Failures'] = MagFailLast[FailureMag]
  MagFailLast[FailureMag] += int(row['Magnet Failure'])
  FailureCon = row['Console failure']
  ConFailLast[FailureCon] +=  int(row['Console failure'])
  DataFull.loc[index,'Console Total Failures'] = ConFailLast[FailureCon]
  FailureDet = row['Detector Failure']
  DataFull.loc[index,'Detector Total Failures'] = DetFailLast[FailureDet]
  DetFailLast[FailureDet] += int(row['Detector Failure'])
  FailureCh1 = row['Channel 1 Failure']
  DataFull.loc[index,'Channel 1 Total Failures'] = Ch1FailLast[FailureCh1]
  Ch1FailLast[FailureCh1] += int(row['Channel 1 Failure'])
  FailureCh2 = row['Channel 2 Failure']
  DataFull.loc[index,'Channel 2 Total Failures'] = Ch2FailLast[FailureCh2]
  Ch2FailLast[FailureCh2] += int(row['Channel 2 Failure'])
  FailureCh3 = row['Channel 3 Failure']
  DataFull.loc[index,'Channel 3 Total Failures'] = Ch3FailLast[FailureCh3]
  Ch3FailLast[FailureCh3] += int(row['Channel 3 Failure'])

DataFull.head()
```

```
# My proposal included many models that I will try to cover and compare they will be done in this section.
#X = DataFull[['Console Total Failures','Rod Drive Total Failures','Motor Total Failures','Magnet Total
Failures','Microswitch Total Failures','Potentiometer Total Failures','Detector Total Failures','Channel 1
Total Failures','Channel 2 Total Failures','Channel 3 Total Failures','Leadscrew Total Failures']]
X = DataFull[['Console Total Failures','Motor Total Failures','Magnet Total Failures','Microswitch Total
Failures','Potentiometer Total Failures','Detector Total Failures','Channel 1 Total Failures','Channel 2
Total Failures','Channel 3 Total Failures','Leadscrew Total Failures']]
# For the scope of this project we are looking for specifically the rod drive.
y = DataFull['Rod Drive Failure']
y = y.astype(int)
# y = DataFull[['Motor Failure']]
# y = DataFull[['Magnet Failure']]
# y = DataFull[['Leadscrew Failure']]
# y = DataFull[['potentiometer failure']]
# y = DataFull[['Microswitch Failure']]
# y = DataFull[['Console failure']]
# y = DataFull[['Detector Failure']]
# y = DataFull[['Channel 1 Failure']]
# y = DataFull[['Channel 2 Failure']]
# y = DataFull[['Channel 3 Failure']]

# k-Nearest Neighbors
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0
averages = []

for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    z_Data = StandardScaler().fit_transform(DataFull)
    z_fit = StandardScaler().fit(X_train)
    z_X_train = z_fit.transform(X_train)
    z_X_test = z_fit.transform(X_test)
    z_X_test
    kNN = KNeighborsClassifier(n_neighbors=5) # Specify k = n_neighbors
```

```
    # I am not sure I understand the warning provided for this one. But it looks to not like something. I would understand it better if it also didn't occur outside of the for loop.
    kNN.fit(z_X_train,y_train)
    pred = kNN.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += kNN.score(z_X_test, y_test)
    r2Train += kNN.score(z_X_train, y_train)
    Rod_Prob_train = kNN.predict_proba(z_X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Rod Failure Probability', np.average(averages))

# Logistic Regression
from sklearn.linear_model import LogisticRegression
import statsmodels.api as sm

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0
averages = []
for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    log_reg = LogisticRegression()
    log_reg.fit(X_train,y_train)
    pred = log_reg.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += log_reg.score(X_test, y_test)
    r2Train += log_reg.score(X_train, y_train)
    Rod_Prob_train = log_reg.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
```

```
print('Average Rod Failure Probability', np.average(averages))

# Naive Bayes

# Guassian Naive Bayes
from sklearn.naive_bayes import GaussianNB

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0

averages = []

for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    gnb = GaussianNB()
    gnb.fit(X_train,y_train)
    pred = gnb.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += gnb.score(X_test, y_test)
    r2Train += gnb.score(X_train, y_train)
    Rod_Prob_train = gnb.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,0]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Rod Failure Probability', np.average(averages))

# Bernoulli Naive Bayes
from sklearn.naive_bayes import BernoulliNB

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0

averages = []
```

```
for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    gnb = BernoulliNB()
    gnb.fit(X_train,y_train)
    pred = gnb.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += gnb.score(X_test, y_test)
    r2Train += gnb.score(X_train, y_train)
    Rod_Prob_train = gnb.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Rod Failure Probability', np.average(averages))

# Multinomial Naive Bayes -- Performed the best
from sklearn.naive_bayes import MultinomialNB

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0

averages = []

for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    gnb = MultinomialNB()
    gnb.fit(X_train,y_train)
    pred = gnb.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += gnb.score(X_test, y_test)
    r2Train += gnb.score(X_train, y_train)
    Rod_Prob_train = gnb.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))
```

```
print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Rod Failure Probability', np.average(averages))

# Auto associative neural network -- Model does not converge due to the lack of data
from sklearn.model_selection import RepeatedKFold
from keras.models import Sequential
from keras.layers import Dense
from keras.callbacks import EarlyStopping, ModelCheckpoint
from sklearn.preprocessing import StandardScaler

cv = RepeatedKFold(n_splits=11,n_repeats=11, random_state=42)

for train_ix, test_ix in cv.split(X):
    X_train, X_test = X.iloc[train_ix], X.iloc[test_ix]
    y_train, y_test = y.iloc[train_ix], y.iloc[test_ix]

#X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

X_train_tr, X_train_v, y_train_tr, y_train_v = train_test_split(X_train, y_train, test_size=1/4,
random_state=42)

model = Sequential()
model.add(Dense(11, kernel_initializer='he_normal', activation='relu'))
model.add(Dense(5, kernel_initializer='he_normal', activation='relu'))
#model.add(Dense(2, kernel_initializer='he_normal', activation='relu'))
#model.add(Dense(5, kernel_initializer='he_normal', activation='relu'))
model.add(Dense(11, activation='linear'))

model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=["accuracy"])

model.fit(X_train_tr, y_train_tr, epochs=200, validation_data=(X_train_v, y_train_v),
callbacks=[EarlyStopping(monitor='val_loss',patience=3, verbose=1, mode='min'), ModelCheckpoint('aann',
verbose=1, save_best_only=True)])
```

```
model.evaluate(X_test, y_test)

# MultinomialNB to predict other values beyond total Failure

# Motor failure
X = DataFull[['Console Total Failures','Motor Total Failures','Magnet Total Failures','Microswitch Total Failures','Potentiometer Total Failures','Detector Total Failures','Channel 1 Total Failures','Channel 2 Total Failures','Channel 3 Total Failures','Leadscrew Total Failures']]
y = DataFull['Motor Failure']
y = y.astype(int)

from sklearn.naive_bayes import MultinomialNB

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0

averages = []

for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    gnb = MultinomialNB(fit_prior=True, class_prior=[(1-(8/119)), 8/119])
    gnb.fit(X_train,y_train.values.ravel())
    pred = gnb.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += gnb.score(X_test, y_test)
    r2Train += gnb.score(X_train, y_train)
    Rod_Prob_train = gnb.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Motor Failure Probability', np.average(averages))

# Magnet failure
```

```
X = DataFull[['Console Total Failures','Motor Total Failures','Magnet Total Failures','Microswitch Total Failures','Potentiometer Total Failures','Detector Total Failures','Channel 1 Total Failures','Channel 2 Total Failures','Channel 3 Total Failures','Leadscrew Total Failures']]
y = DataFull[['Magnet Failure']]
y = y.astype(int)

from sklearn.naive_bayes import MultinomialNB

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0

averages = []

for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    gnb = MultinomialNB()
    gnb.fit(X_train,y_train.values.ravel())
    pred = gnb.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += gnb.score(X_test, y_test)
    r2Train += gnb.score(X_train, y_train)
    Rod_Prob_train = gnb.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Magnet Failure Probability', np.average(averages))

# Leadscrew Failure
X = DataFull[['Console Total Failures','Motor Total Failures','Magnet Total Failures','Microswitch Total Failures','Potentiometer Total Failures','Detector Total Failures','Channel 1 Total Failures','Channel 2 Total Failures','Channel 3 Total Failures','Leadscrew Total Failures']]
y = DataFull[['Leadscrew Failure']]
y = y.astype(int)

from sklearn.naive_bayes import MultinomialNB
```

```
r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0

averages = []

for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    gnb = MultinomialNB()
    gnb.fit(X_train,y_train.values.ravel())
    pred = gnb.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += gnb.score(X_test, y_test)
    r2Train += gnb.score(X_train, y_train)
    Rod_Prob_train = gnb.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Leadscrew Failure Probability', np.average(averages))

# Potentiometer Failure
X = DataFull[['Console Total Failures','Motor Total Failures','Magnet Total Failures','Microswitch Total 
Failures','Potentiometer Total Failures','Detector Total Failures','Channel 1 Total Failures','Channel 2 
Total Failures','Channel 3 Total Failures','Leadscrew Total Failures']]
y = DataFull[['potentiometer failure']]
y = y.astype(int)

from sklearn.naive_bayes import MultinomialNB

r2Test = 0
r2Train = 0
rmse_values = 0
Rod_Prob_train = 0

averages = []
```

```
for i in range(100):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/5)
    gnb = MultinomialNB()
    gnb.fit(X_train,y_train.values.ravel())
    pred = gnb.predict(X_test)
    rmse_values += mean_squared_error(y_test,pred,squared=False)
    r2Test += gnb.score(X_test, y_test)
    r2Train += gnb.score(X_train, y_train)
    Rod_Prob_train = gnb.predict_proba(X_test)#[:,1]
    averages.append(np.average(Rod_Prob_train[:,1]))


print('Training accuracy: ', r2Train/(i+1))
print('Testing accuracy: ', r2Test/(i+1))
print('Mean Squared: ', rmse_values/(i+1))
print('Average Potentiometer Failure Probability', np.average(averages))

# Validation
# To validate the models the following data was found that show the statistics for a control rod drive
failure within a reactor, through the observed failures of over many demands / hours.
Expected = pd.read_csv('https://gitlab.com/WickedWess/cs-final-rod-drive-risk/-
/raw/main/Final_Project_Estimates.csv')
Expected.head()

import seaborn as sb
plt.subplots(figsize=(10,10))
dataplot = sb.heatmap(DataFull.corr(), annot=True)
plt.show()

# Statistics stuff that is not machine learning
Demands = DataFull.shape[0]
#print(Demands)
Failures = DataFull[DataFull['Rod Drive Failure'] == 1].shape[0]
#print(Failures)
alpha = Failures + 0.5 # then number of failed demands + 0.5
beta = 3652.5 # Amount of time in time units (days)
mean_gamma = alpha / beta
std_gamma = alpha / (beta * beta)
print('Mean of resultant gamma distribution', mean_gamma)
```

```
print('Standard deviation of resultant gamma distribution', std_gamma)
Gamma_acc = math.sqrt((mean_gamma-Expected['Mean'][2])/2)
per_error = mean_gamma-Expected['Mean'][2]/Expected['Mean'][2]
print("% error", per_error)
print("RSME of Gamma",Gamma_acc)

# MORE Statistics stuff that is not machine learning
Demands = DataFull.shape[0]
#print(Demands)
Failures = DataFull.shape[0]
#print(Failures)
alpha = Failures + 0.5 # then number of failed demands + 0.5
beta = 3652.5 # Amount of time in time units (days)
mean_gamma = alpha / beta
std_gamma = alpha / (beta * beta)
print('Mean of resultant gamma distribution', mean_gamma)
print('Standard deviation of resultant gamma distribution', std_gamma)
Gamma_acc = math.sqrt((mean_gamma-Expected['Mean'][2])/2)
per_error = mean_gamma-Expected['Mean'][2]/Expected['Mean'][2]
print("% error", per_error)
print("RSME of Gamma",Gamma_acc)

# Math for the magnets
Demands = DataFull.shape[0]
#print(Demands)
Failures = DataFull[DataFull['Magnet Failure'] == 1].shape[0]
#print(Failures)
alpha = Failures + 0.5 # then number of failed demands + 0.5
beta = 3652.5 # Amount of time in time units (days)
mean_gamma = alpha / beta
std_gamma = alpha / (beta * beta)
print('Mean of resultant gamma distribution', mean_gamma)
print('Standard deviation of resultant gamma distribution', std_gamma)
Gamma_acc = math.sqrt((mean_gamma-Expected['Mean'][2])/2)
per_error = mean_gamma-Expected['Mean'][2]/Expected['Mean'][2]
print("% error", per_error)
print("RSME of Gamma",Gamma_acc)

# Math for the Leadscrews
Demands = DataFull.shape[0]
```

```
#print(Demands)
Failures = DataFull[DataFull['Leadscrew Failure'] == 1].shape[0]
#print(Failures)
alpha = Failures + 0.5 # then number of failed demands + 0.5
beta = 3652.5 # Amount of time in time units (days)
mean_gamma = alpha / beta
std_gamma = alpha / (beta * beta)
print('Mean of resultant gamma distribution', mean_gamma)
print('Standard deviation of resultant gamma distribution', std_gamma)
Gamma_acc = math.sqrt((mean_gamma-Expected['Mean'][2])/2)
per_error = mean_gamma-Expected['Mean'][2]/Expected['Mean'][2]
print("% error", per_error)
print("RSME of Gamma",Gamma_acc)

# Math for the motor
Demands = DataFull.shape[0]
#print(Demands)
Failures = DataFull[DataFull['Motor Failure'] == 1].shape[0]
#print(Failures)
alpha = Failures + 0.5 # then number of failed demands + 0.5
beta = 3652.5 # Amount of time in time units (days)
mean_gamma = alpha / beta
std_gamma = alpha / (beta * beta)
print('Mean of resultant gamma distribution', mean_gamma)
print('Standard deviation of resultant gamma distribution', std_gamma)
Gamma_acc = math.sqrt((mean_gamma-Expected['Mean'][2])/2)
per_error = mean_gamma-Expected['Mean'][2]/Expected['Mean'][2]
print("% error", per_error)
print("RSME of Gamma",Gamma_acc)…
```