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Safety Critical I&C Component Inventory Management Method for Nuclear Power Plant using Linear Data Analysis Technic

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Abstract : This paper aims to develop an optimized inventory management method for safety critical Instrument and Control (I&C) components. In this regard, the paper focuses on estimating the consumption rate of I&C components using demand forecasting methods. The target component for this paper is the Foxboro SPEC−200 controller. This component was chosen because it has highest consumption rate among the safety critical I&C components in Korean OPR−1000 NPPs. Three analytical methods were chosen in order to develop the demand forecasting methods; Poisson, Generalized Linear Model (GLM) and Bootstrapping. The results show that the GLM gives better accuracy than the other analytical methods. This is because the GLM considers the maintenance level of the component by discriminating between corrective and preventive.

Key Words : Inventory Management Method, Linear Data Analysis, Poisson, Generalized Linear Model (GLM), Bootstrapping, Safety Critical I&C, SPEC−200 controller, Nuclear Power Plant

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1. Introduction

1.1 Background

In operating nuclear power plants, it is important to have an adequate number of spare parts specifically for safety related systems. In accordance with Technical Specification (Chapter 16 of FSAR), the repair time of safety critical I&C component is set for two (2) hours. Inventory management of such component is a crucial criterion. If it is not met, whenever such component fails, and repairs are required, the nuclear plant might be shut down as a result of inefficient inventory management. To cope with this tough condition, maintenance personnel gives higher priority to the availability of such component. This prioritization results in inefficient spare parts management which results in high maintenance cost.

The accurate forecast of needed spare parts can be challenging under the conditions of intermittent demand, low failure rates and high consequences of stockout [1]. Due to these difficulties, there are no models for forecasting spare parts for OPR-1000 NPPs. If the spare parts are not supplied in a timely manner, the availability of the power plant may be reduced. As a rule of thumb, the more accurate the demand forecast, the more the plant efficiency is enhanced.

Optimized inventory management will enable efficient operation. Low forecasting accuracy of number of spares needed may make it difficult to ensure that the plant's resources are efficiently utilized. Low forecasting accuracy may cause shortage of parts (or inventory) or cause budget losses due to excess inventory. This is an important part in terms of ensuring plant utilization rates and efficient budgeting. As such, it can be said that improving the accuracy of demand forecasting is the basis for maintaining proper inventory. However, intermittent demand is one of the main reasons making forecasting demand is difficult.

Electric Power Research Institute (EPRI) presented several technical reports that support optimization of inventory of spare parts in a nuclear utility [2], [3]. However, it is difficult to apply to operating plants because it depends on overseas inventory procurement conditions and available models can not apply directly without modification [4].

Some companies use the Economic Order Quantity (EOQ) model, which is a classic model in production/operational management used to calculate the appropriate number of spare parts required. In addition, the Advanced-EOQ model, which is an improvement to the EOQ model is also used in consideration of unique areas such as nuclear power plants [5].

However, in domestic nuclear power plants, this work is still done manually through the experience and intuition of field engineers. Therefore, spare parts should be carefully purchased in consideration of the importance and characteristics of the equipment, and the accurate inventory algorithm should be applied to the appropriate level of spare parts

1.2 Forecast of Intermittent Demand

In the past, demand was predicted using a qualitative method. Then, demand forecast was attempted using time series methods such as moving average, exponential smoothing or causal models such as regression [6]. Especially, exponential smoothing method is a very popular method and has been one of the standards in forecasting demands [7]. Spare parts in nuclear power plants are typically used intermittently, so these methods have shown low accuracy because it does not consider the intermittent demand which does not follow normal distribution and is not well forecasted by the usual time series methods. There are not so many methods to deal with intermittent demands. In 1972, Croston proposed a time series prediction method that modified exponential smoothing [8]. Syntetos and Boylan presented an improved method for the bias problem occurring with the Croston method [9]. In addition, there have been studies on how to use bootstrapping utilization and distribution [10].

1.3 Prognosis of Demand

According to the IEC 62550, there are three categories of demand forecast procedures [11].

- Deterministic procedures;
- Statistical analysis based on consumption data;
- Subjective estimation.

Deterministic procedures are used when the demand for future periods can be forecast with good precision. An inventory policy can be developed in order to satisfy all spare parts requests. On the other hand, when it is not possible to forecast future demand with acceptable precision, statistical analysis is used. These models assume that future demand is a random variable having a known probability distribution. The inventory policy is designed based on the service level desired. Service level is the percentage of spare parts requests that are satisfied immediately.

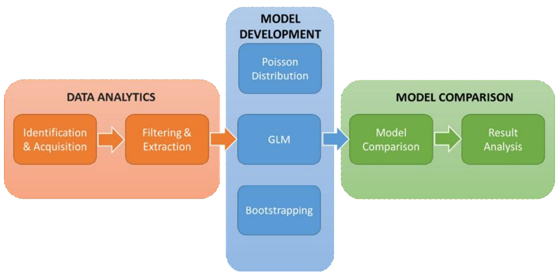
2. Develop the Model for Optimum Inventory Management

The framework developed in this paper is divided into three stages; data analytics stage, model development stage and model comparison stage as represented in Figure 2. It aims at bringing out an optimal demand forecasting model based on the consumption data of spare parts.

2.1 Data Analytics Routine

2.1.1 Define Input Data

In this paper, five (5) different type of controllers of the SPEC 200 card are analyzed for defining static availability. Table 1 shows the calculated Mean Time between Failure (MTBF) and static availability for the SPEC 200 controllers. Static availability for each product is



[Figure 1] Model development framework

<Table 1> SPEC 200 Data

2AO−L2 C−R	Contact Output Isolator	2813	0.5	0.0004	0.99999 998
N−2AO−V2I	Voltage to Current Converter	3463	0.5	0.0003	0.99999 998
N−2ARP S05	Multi nest power supply	336	0.5	0.0030	0.99999 983
N−2AX	Multiplier	3680	0.5	0.0003	0.99999 998

defined by Equation (1)

$$A_{ss} = \frac{MTBF}{MTBF+MTTR} \quad (1)$$

Where, MTTR which is defined as the time required on average to detect a failed element within the system and complete the actions necessary to restore full system function. The MTTR for the SPEC 200 card is specified for half (0.5) hours for the conservatism of the analytic results.

Data analytics stage is dedicated to identifying the consumption datasets of process controller (SPEC-200). The acquired data from NPP maintenance experience is filtered to remove the inappropriate data or worthless data. For the purpose of applying data filtering and extraction, two mathematical functions are utilized; weighted moving average and exponential smoothing. As shown in Equation (2), weighted moving average applies different weights for specific planning periods.

$$P_i = \frac{1}{n}\sum_{k=1}^{n} \omega_k . d_{i-k} \quad (2)$$

When similar impacts are present on a regular period, higher weights can be applied to the values of that period. If there is a large demand for spare parts during the predictive outage period every 18 months, a higher weight can be applied to the value of that period.

On the other hand, exponential smoothing function is suitable for forecasting data with no clear trend or seasonal pattern [12]. It is a technique that can be applied to time series data to make forecasts. The procedure does not require all individual values of the past but only three data elements are required; the previous planning period ($P_{predicted,old}$), actual demand for the previous planning period ($P_{actual,old}$), and smoothing function (α) which is specified as values between 0 and 1. Equation (3) shows the exponential smoothing by the first order function.

$$P_{new} = P_{predicted,old} + \alpha(P_{actual,old} - P_{predicted,old}) \quad (3)$$

The new prognosis P_{new} is computed from the preceding prognosis $P_{predicted,old}$, corrected by the product of the smoothing coefficient a and the difference between the actual and predicted demand of the preceding planning period.

2.2 Model Development Routine

In this stage, the demand forecasting models which are Poisson distribution, GLM, and bootstrapping, are used.

2.2.1 Poisson distribution model

The Poisson distribution is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time or space if these events occur with a known constant rate and independently of the time since the last event [13]. According to the IEC 62550, if the value (λT), average number of demands during a given time T, is smaller than 50, the Poisson distribution can be used for sparing model [11]. The Poisson distribution can be applied when some measure is continuous while the number of events which may occur during this continuous random variable is established by counting. It can be applied when the probability of occurrence is very small. This is the case when the time interval is long and/or the demand rate is low.

2.2.2 General Linear Model (GLM)

GLM is a generalization of the linear regression model that enables a model to be defined for an output variable that is not normally distributed. GLM uses a link function or canonical function to define the relationship between the predictor and the response variables. Since the failure rate of the cards follows Poisson distribution, the link function is given as Equation (2).

$$\log(\mu) = Xb \quad (4)$$

where, μ is the response variable, X is the predictor variable vector and b is the coefficient matrix.

Two cases of the GLM are investigated. The first case computes the relationship between the parameters and the quantity of spares at each interval of time. The second case investigates the effect of cumulative quantity of spares on model performance.

The GLM can be expressed as indicated in equation (5).

$$log(Qty) \sim ModelNum + MTBF + Mtype + Uptime \quad (5)$$

where, *ModelNum* is the installation quantity of specific controller, *Mtype* is the maintenance type (either corrective or preventive).

GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value.

2.2.3 Bootstrapping Model

Hua et al. suggested that when historical data are limited, the bootstrap method is a useful tool to estimate the demand of spare parts [14]. Bookbinder and Lordahl found the bootstrap superior to the normal approximation for estimating high percentiles of spare parts demand for independent data [15]. Wang and Rao also found the bootstrap effective to deal with smooth demand [16]. All these papers do not consider the special problems of managing intermittent demand. Willemain et al. provided an approach of forecasting intermittent demand for service parts inventories [17]. They developed a bootstrap-based approach to forecast the distribution of the sum of intermittent demands over a fixed lead time. One standard choice for an approximating distribution is the empirical distribution of the observed data. This method can be applied not only to find the average demand (that can be the demand forecast) but also the intervals between non zero-demand or other desired values.

2.3 Model Comparison Routine

After developing these models, the models are estimated and compared in model comparison stage. Root Mean Squared Error (RMSE) and R-squared which are frequently used measures are utilized to estimate the suitability of the model.

The RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data, that is, how close the observed data points are to the predicted values of the model. Since RMSE is an absolute measure of fit, lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response, and it is the most important criterion for fit if the main purpose of the model is prediction [18][19]. The RMSE is computed as shown in equation (6).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f_i)^2} \quad (6)$$

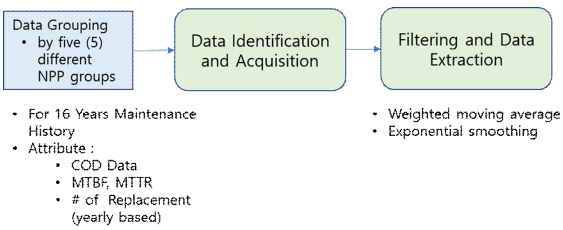
3. Implementation of Inventory Optimization Model

3.1 Execution of Data Analytics Routine

As discussed in Chapter 2, the proposed model is divided into three stages; data analytics, model development, and model comparison. The data analytics stage can be described in two stages; the first stage is data identification and acquisition while the second is filtering and data extraction. Figure 3 shows the scheme implemented for the data analytics stage.

3.1.1 Data Identification and Acquisition Stage

The data is a collection of six plant sites. The plants are labelled from A to F for anonymousity. Each plant site consists of two units. Each plant site has different commercial



[Figure 2] Scheme of Data Analysis Routine

operation date (COD). The quantity of the installed SPEC 200 is the same for all units because this data is obtained from OPR-1000 units.

3.1.2 Data Filtering Stage

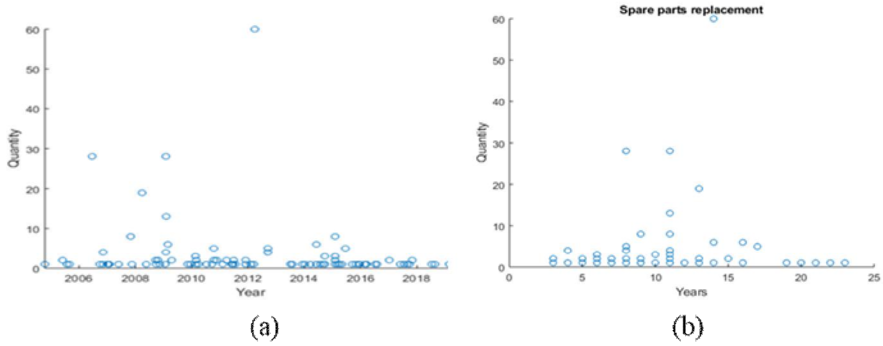
Usually, data entries often contain errors. The objective of preprocessing is to remove or reduce these errors before using the data in any model development. Entries such as date must be formatted appropriately. Visualization of the data shows that the part replacement date and the COD columns needed to be reformatted.

Summary report of the data shows the minimum replacement quantity of 1 and a maximum replacement quantity of 60. The median replacement quantity is also 1 which is an indication of an average small quantity of part replacements per maintenance work. Also, the replacement history spans from 2004 to 2019 which is a period of 16 years.

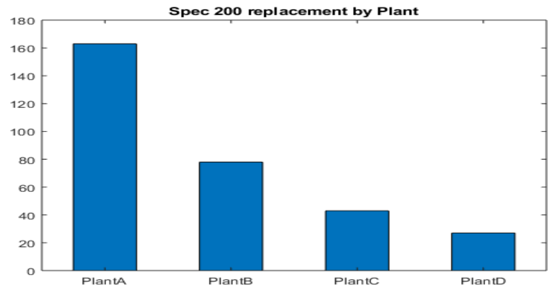
Figure 3(a) shows that the quantities of parts replaced during the 16 years of maintenance work are between 1 and 10 quantities. Some records show that replacement quantities are between the range of 10 to 30 and a very few record shows replaced parts up to 60. It implies the nominal quantity needed for corrective maintenance actions will fall into the largest cluster of 1 to 10 quantities.

The other two clusters indicate a situation in which both corrective and preventive actions were taken.

Also, some plant site record does not span the 16 years record in view. This is processed by removing the plant records that do not cover the 16 years analysis period in view



[Figure 3] Spare part replacement history for all plant sites (a) before data filtering (b) after data filtering



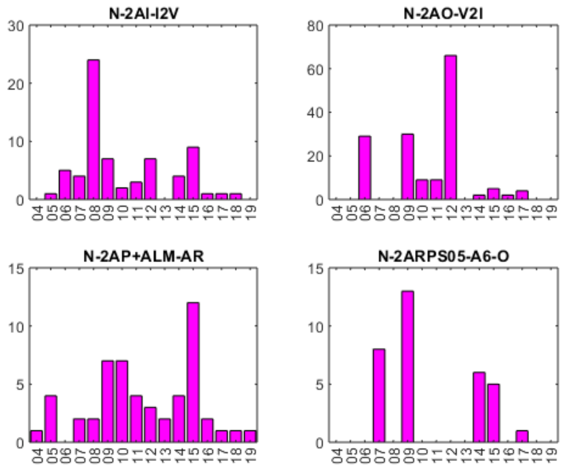
[Figure 4] Spares by plant sites

<Table 2> Installed Quantity versus Average Stored part per Controller Model (all plants)

	Model No	Install Qty	Avg. Spare
1	'N-2AI-I2V'	656	4.3125
2	'N-2AO-V2I'	1696	9.75
3	'N-2AP+ALM-AR'	240	3.3125
4	'N-2ARPS05-A6-O'	48	2.0625

(2004 to 2019). Figure 4(b) depicts the part replacement data after filtering by weighted moving average, and exponential smoothing.

Figure 4 shows the plant data which were aggregated and visualized by plant types. From the plot, plant site A consumed the largest SPEC 200 spare part and plant site D consumed the least. Also, the N-2AO-V2I card represents the highest average spare replacement across all plants as shown in Table 2. It indicates data for installed quantity versus average stored spart-part per controller model for all

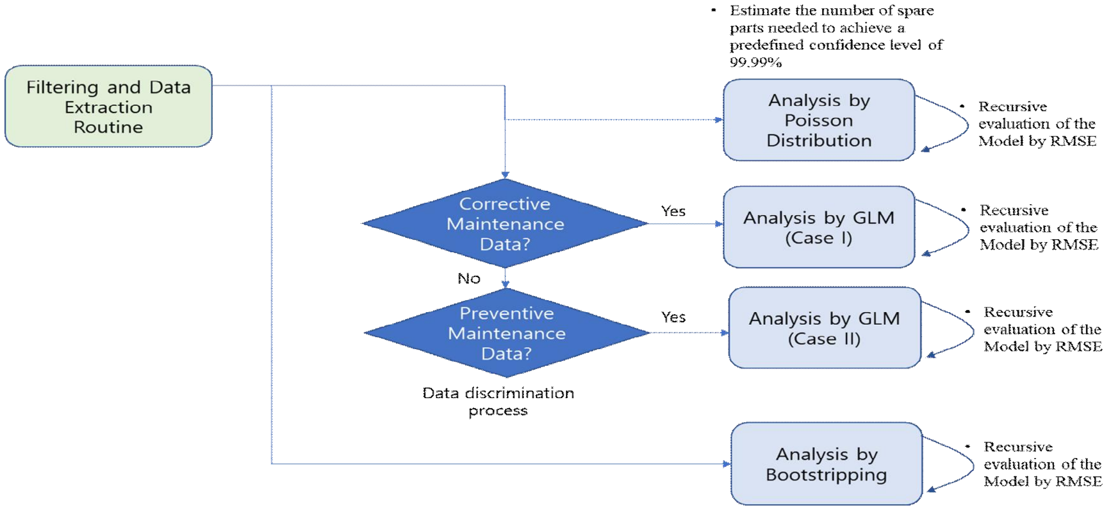


[Figure 5] Distribution of spare-parts per model of controller for all plant sites

plants. In Figure 5, the distribution of spare-part per model of controller for all plant sites is shown. The distribution is how many sets of specific controller were acquired from Korean NPPs. This information is the sum of each NPP group. So, the statistics is plant specific.

3.2 Test of Developed Model Routine

Figure 6 shows how the model development routine is deployed in this work. The tool used for developing these models is MATLAB. The models are tested using plant data as previously described. The models are implemented in the following sections.



[Figure 6] Flow diagram of model development routine

3.2.1 Poisson Distribution Model

The Poisson distribution is used quite often in sparing analysis. The occurrence of failed components and the demand for spares are events that can be described by Poisson distribution when they occur at a constant average rate and when the number of events/failures at one instance of time are independent of the number of events at any other interval/instance of time. The results of this batch processing is represented by the format of contingency table as Table 3.

With lead time t=3 years, the cumulated failure rate, per specific controller is;

<Table 3> Contingency Table

Spares (n)	Confidence Level	P_I2V	P_V2I	P_ALM	P_PS
0		0.6251	0.2301	0.7742	0.6514
1		0.9188	0.5682	0.9723	0.9306
2		0.9878	0.8165	0.9977	0.9905
3	$\sum_{k=0}^{n}\frac{((N\lambda t)^k e^{-N\lambda t})}{k!}$	0.9986	0.9382	0.9999	0.9990
4		0.9999	0.9828	1.0000	0.9999
5		1.0000	0.9960	1.0000	1.0000
6		1.0000	0.9992	1.0000	1.0000
7		1.0000	0.9999	1.0000	1.0000

For I2V card: $N\lambda t = \frac{N*t}{MTBF} = \frac{(656*3)}{4189} = 0.4698$

For V2I card: $\lambda t = \frac{N*t}{MTBF} = \frac{(1696*3)}{3463} = 1.4692$

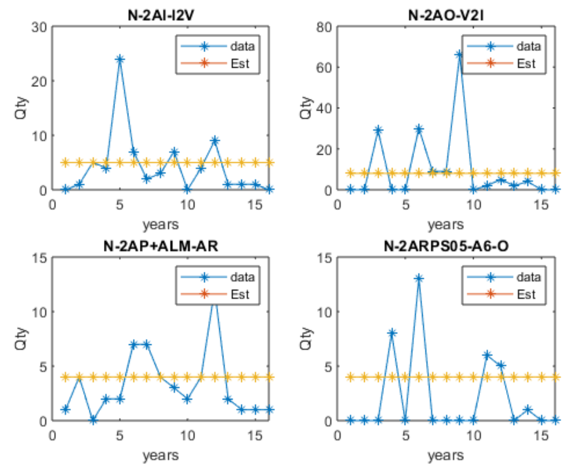
For ALM card: $N\lambda t = \frac{N*t}{MTBF} = \frac{(240*3)}{2813} = 0.2560$

For PS card: $N\lambda t = \frac{N*t}{MTBF} = \frac{(48*3)}{336} = 0.4286$

A. Evaluation of Poisson Model

Figure 7 shows the plot of the estimated spare versus the actual data for each card type.

In order to evaluate the model, the Root



[Figure 7] Estimated spare versus Actual data

<Table 4> RMSE for SPEC 200 Cards (Poisson)

	Model No	RMSE
1	'N-2AI-I2V'	5.8041
2	'N-2AO-V2I'	17.9374
3	'N-2AP+ALM-AR'	3.4369
4	'N-2ARPS05-A6-O'	4.7762

Mean Squared Error (RMSE) measure is used. Table 4 represents the computed RMSE values for the SPEC 200 cards. There is a large error between calculated values and the real observed value from data set. Table 4 indicates RMSE for SPEC 200 Cards for Poisson distribution.

The specific reason why these results were brought out, was that the observed values did not exclusively represent failed components. Therefore, the effects either failure rate or MTBF may not be affected by the observations. The Average RMSE of this model is calculated as;

Average RMSE = mean (RMSE) = 7.9887

3.2.2 Generalized Linear Model (GLM)

A. CASE 1: Classification by maintenance types

This case separates the maintenance actions into three groups:

- Corrective maintenance: 1~15 spares
- Corrective maintenance and preventive maintenance: 15~30 spares
- Corrective maintenance and more preventive: more than 30 spares

The rationale for this is that the real failure rate of SPEC 200 is low. However, it is common to replace associated cards that are in line with the defective card so that the entire system is restored to default condition and the root cause of the failure is eliminated altogether. The estimated coefficients is given below along with the p-value:

<Table 5> Estimated coefficients (GLM Case 1)

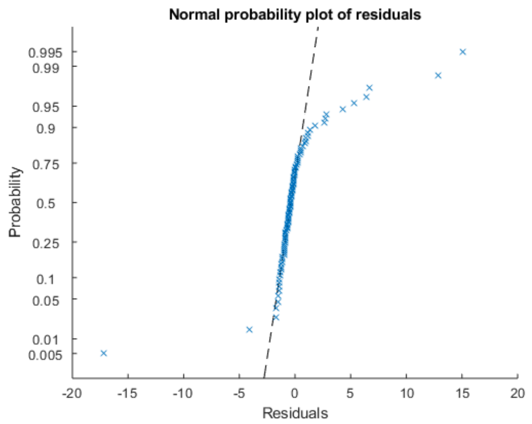
Predictor Variable	Coefficient	p-Value
ModelNum_N-2AO-V2I	-0.19647	0.23391
ModelNum_N-2AP+ALM-AR	-0.6495	5.1391e-05
ModelNum_N-2ARPS05-A6-O	0.72676	0.0057511
MTBF	-0.00016173	0.0015068
Mtype	1.9434	9.673e-88
Uptime	-0.051963	0.0029278

Except for the p-values of the first term in the Table 5 above, the p-values of the other terms are lower than 0.05. This means that these predictor variables are significant in predicting the quantity of spares using this model. The Estimate values in the table are the values of the coefficient matrix for the GLM.

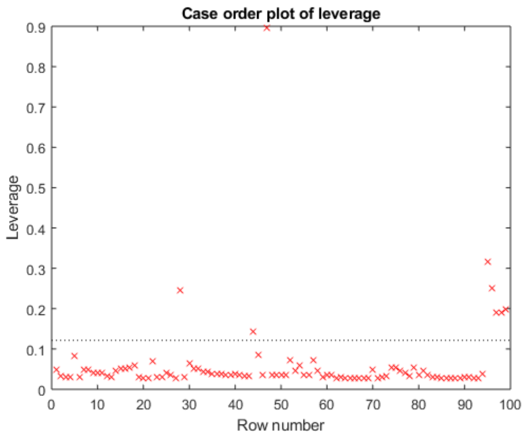
A-1. Evaluation of GLM Case 1

Figure 8 shows the Q-Q plot of GLM case 1. Since most of the points on the Q-Q plot approximately laid on the straight line, then the residuals are to be distributed normally. Although, some points wonder off the line. The histogram also shows that the residual is normally distributed with mean residual value which is distributed to zero region. Also, the leverage plot shows the distribution of the residuals around zero value and that it is mostly positively biased.

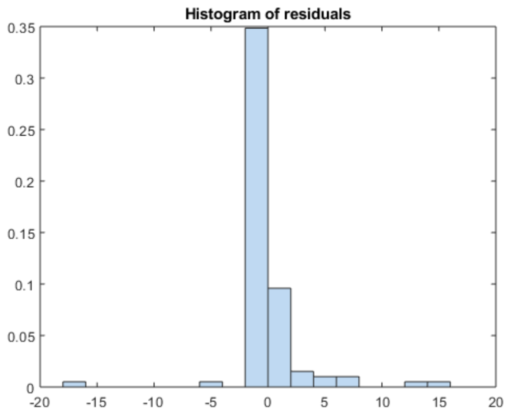
From Figure 8 to 10 depict the normal probability plot of residuals, histogram of residuals and order plot of leverage for GLM case 1 respectively.



[Figure 8] Normal probability plot of residuals (GLM case 1)



[Figure 10] Order plot of leverage (GLM case 1)



[Figure 9] Histogram of residuals (GLM case 1)

The calculated R−squared Value and adjusted R−squared value of this model are:

- R−squared = 0.8229
- Adjusted R−squared = 0.9933

<Table 6> GLM case 1 results

GLM Case	R−Squared	Adjusted R−Squared	RMSE
Case 1	0.8229	0.9933	3.0527

The calculated RMSE value of this model is: 3.0527.

A−2. CASE 2: Cumulating replacement

In this case, the replacement quantity is changed to the cumulative replacement quantity. This is because the cumulative replacement quantity over the uptime can be a major variable.

B. Evaluation of GLM Case 2

Figure 11 shows the Q-Q plot in case of

<Table 7> Estimated coefficients (GLM 2)

<Table 7> Estimated coefficients (GLM 2)

```
Generalized linear regression model: log(Qty) ~ ModelNum + MTBF + Mtype + Uptime
Distribution = Poisson

                              Estimate        SE         tStat        pValue
                             __________    ________    ________    __________
ModelNum_N-2AO-V2I              0.58952     0.06427     9.1726      4.6156e-20
ModelNum_N-2AP+ALM-AR           0.30469    0.060748     5.0156      5.2878e-07
ModelNum_N-2ARPS05-A6-O         0.59215     0.13712     4.3186      1.5701e-05
MTBF                         0.00013063    2.86e-05     4.5674       4.939e-06
Mtype                           0.97758    0.039761     24.587     1.7603e-133
Uptime                         0.010003   0.0081362     1.2294         0.21893
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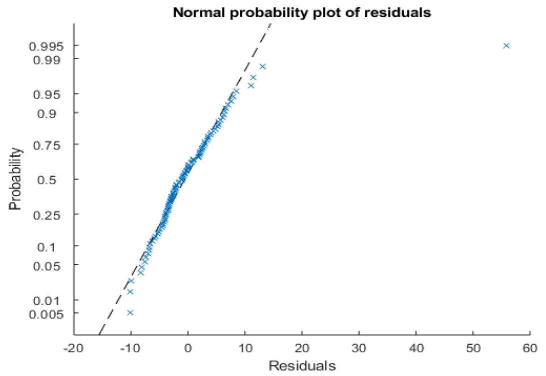
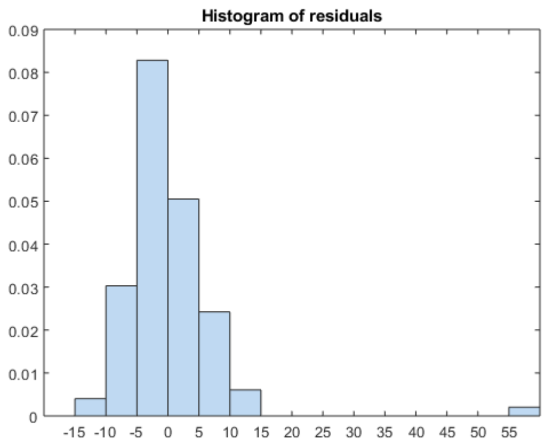


[Figure 11] Normal probability plot of residuals (GLM case 2)

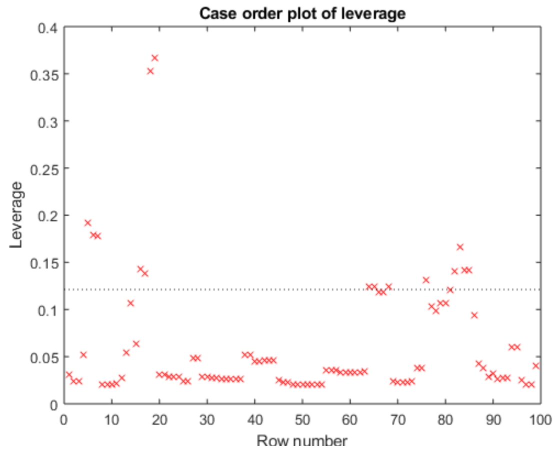


[Figure 12] Histogram of residuals (GLM case 2)

cumulating replacement of spare parts. Since the points on the Q-Q plot approximately lie on the straight line, the residuals are normally distributed. The histogram shown in Figure 12 also shows the normal distribution of the residuals. The leverage plot shows the distribution of the residuals around zero value. The test of a good model is one with normally distributed residuals. This means that the mean residual value is close to 0 and the variance is not more than 1.

The calculated R-squared Value and adjusted R-squared value of this model are:

- R-squared = 0.7958
- Adjusted R-squared = 0.7848



[Figure 13] Case order plot of leverage (GLM case 2)

<Table 8> GLM case 2 results

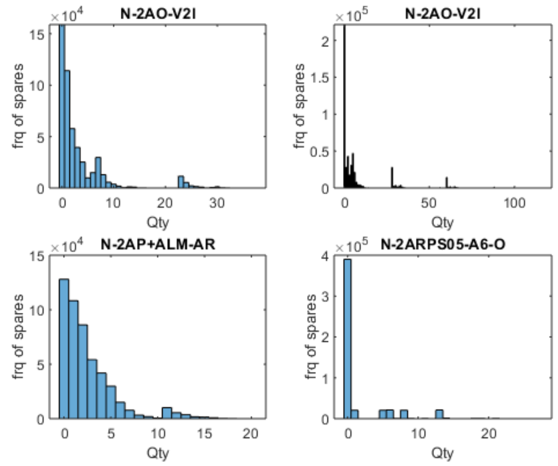
GLM Case	R-Squared	Adjusted R-Squared	RMSE
Case 2	0.7958	0.7848	7.4390

The calculated RMSE value of this model is: 7.4390 as indicated in Table 8.

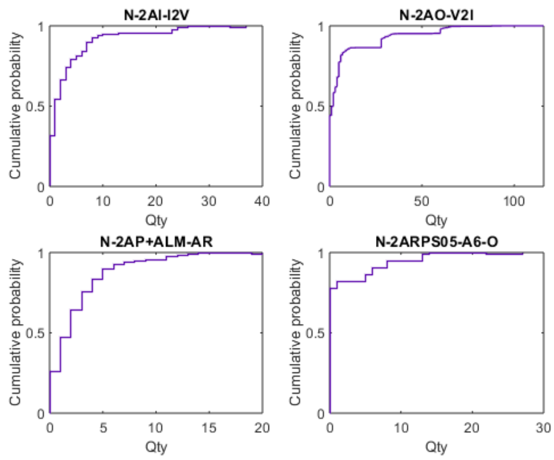
3.2.3 Bootstrapping Model

The bootstrap approach is to resample from the 16 years spare replacement data, with replace-ment, three times, creating a bootstrap scenario of total demand over the three-year lead time. This process is then repeated several times to build a statistically rigorous picture of the entire distribution of possible lead-time demand values for each part item.

Figure 14 shows the results of 500,000 bootstrap scenarios. The histograms indicate that the most likely value for lead-time demand is zero (0), but that lead-time demand could be as great as 50 or more units. A cumulative probability density function is constructed such that the value of spares that corresponds to the confidence level of 99.99% is taken as the model estimation result. Figure 15 depicts the



[Figure 14] The results of 500,000 bootstrap scenarios



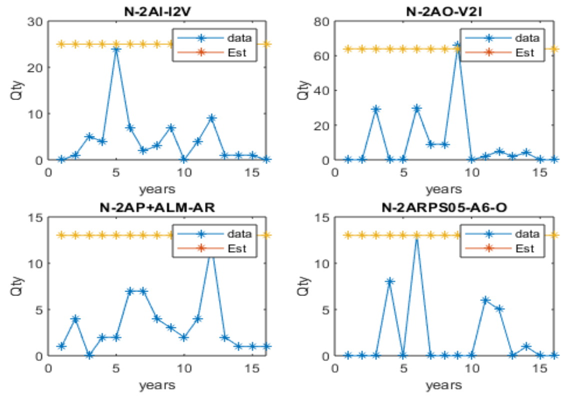
[Figure 15] Cumulative distribution plot

cumulative distribution plot for each card type based on the histogram of the bootstrapped samples.

A. Evaluation of Bootstrapping model

Figure 16 shows the plot of the estimated spare versus the actual data for each card type. In order to evaluate the model, the Root Mean Square Error (RMSE) measure is used. The RMSE is shown in Table 9.

Table 9 shows the computed RMSE values for the SPEC 200 cards using the bootstrap method. There is a large error between calculated



[Figure 16] Estimated spare versus Actual data

<Table 9> RMSE for SPEC 200 cards (Bootstrapping)

	Model No	RMSE
1	'N−2AI−I2V'	21.475
2	'N−2AO−V2I'	56.94
3	'N−2AP+ALM−AR'	10.14
4	'N−2ARPS05−A6−O'	11.568

values and the real observed value from data set. Just like the case of the Poisson distribution, the observed values do not exclusively represent failed components and the effect of failure rate or MTBF cannot be observed. Typically, during maintenance activities it is common to replace other components that are in line with the failed components to ensure that that the root cause is eliminated.

Also, it is common during troubleshooting to replace associated components in other to cut down repair time. Unlike the Poisson method, bootstrap estimates are higher than the actual values. This can guarantee that spares will always be available to assure 99.99% available. However, it is not optimum as it can lead to hold down of capital and high inventory cost.

Average RMSE value of the bootstrapping method can be computed by calculating the mean RMSE and the value obtained was 31.3850.

4. Result of Model Development

The first model (Poisson distribution) is based on the assumption that the data can be described by a Poisson distribution and that failure of components occurs on an average failure rate. The model has large root mean square error indicating that it is not a very good model that can fit the data accurately. Also, the model does not account for the different maintenance types carried out.

The second model utilized the generalized linear regression model. This method allows for modelling of the different types of maintenance work. The first case of the GLM estimates the quantity of spares needed at an instance of time. The second case returns the cumulative quantity needed over the uptime period. In comparison, using the R-squared statistic, the first GLM case returned an R-squared value of 0.8229 which is better than the second GLM case of R-squared value of 0.7958.

The third model uses bootstrap statistics. Bootstrapping in a statistical method of generate many samples from small sample size. In this method, the sample size will be expanded thereby making estimates closer to the population values. The method evaluates the cumulative distribution function (CDF) of the bootstrapped spare quantity for each card. The cumulative quantity that corresponds to the 99.99% cumulative probability is taken as the quantity of spares required to achieve 99.99% confidence level within the lead time of 3 years.

The comparison table for the three types of model is indicated in Table 10. The GLM model for case 1 has the lowest RMSE value and is considered as the best model between the three. This is expected because it considered the maintenance level whether corrective or preventive unlike the other two models which did not consider the maintenance level.

<Table 10> The comparison table

	POISSON	GLM	BOOT STRAPPING
RMSE	7.9887	3.0527	31.3850

5. Conclusion and Further Study

At present, Korean NPP utility company is implementing Material Resource Planning (MRP) system for effective operation of plants. However, purchasing spare parts based on engineer's know-how without considering the optimal spare parts based on the data can cause economic loss or threaten safety of nuclear power plant due to failure of maintaining proper inventory.

Optimal sparing model which forecasts the demand of intermittent spare parts in nuclear power plant is proposed using big data analytics in this research. After analyzing and comparing Poisson method, generalized linear regression method, and bootstrapping method, the optimal demand forecasting model is selected. In addition, since it is based on actual consumption data, it can be said that it is more accurate than the estimated demand by the engineer's know-how. With the results of this research, field engineers can calculate the appropriate spare part quantity for each material and can identify when to buy.

The results in this work show that among those three analytical methods, GLM gives the best accuracy than the other methods, because it considers the maintenance level of the component by discriminating its maintenance period either from corrective or preventive.

As for the further study, the linear regression method will be applied for the analysis of the forecasting demand. In addition, developing non-linear regression model using artificial neural networks (ANN) to improve accuracy will be conducted.

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