IoT-based Dynamic Demand Forecasting Measures

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Abstract: - Markets continue to change, and the speed of such change is becoming faster than ever. In order to adapt to the changing markets, corporations have placed a greater emphasis on supply chain management (SCM). Demand forecasting, being the cause of all factors that constitute SCM, is the most crucial factor. Therefore, it is essential to have a dynamic demand measuring method, so that companies could to adapt to the continuous market changes, and carry out market and demand predictions. Predicting the future based on a vast amount of information on diverse areas is one of the unique means for forecasting. Moreover, it has been proven that the forecasts are more accurate when there is more information with greater diversity. The advent of the IoT (Internet of Things) technology and the era of big data have provided humans with more information on diverse areas. This research aims to utilize the IoT technology and big data for an accurate forecast of the intermittent demand, which has been a difficult area for prediction until now. Moreover, the paper presents a platform that can contribute to effective inventory management and production planning through intermittent demand forecasting.

Key-Words: - IoT, demand forecasting, artificial neural network, failure forecasting, recurrent artificial neural network, changing need, intermittent demand

1 Introduction

With the intense competition in today's society, companies are putting a greater focus on dynamically reacting to the needs of customers through supply chain management (SCM) [1]. As a factor that directly affects SCM, demand prediction is the cause of all activities that occur within the management system [2]. While accurate demand forecasting requires the reflection of the complex managerial environment, it is difficult to consider the entire managerial environment as of now. The non-linear managerial environment is considered as linear environment; therefore, it is difficult to accurately forecast the demand.

Even though intermittent demand forecasting, an area that has been difficult so far, can be performed by using exponential smoothing and Weibull distribution to extract the expected values, it is impossible to accurately predict the demand at a certain point in time. However, as there are frequent requirements for the information on demand at particular points in time, predicting the intermittent demand is a crucial aspect of SCM.

This research proposes a new method of demand prediction, which utilizes IoT data to predict the intermittent demand. Intermittent demand prediction, coupled with IoT technology can accurately forecast the changing needs at specific points in time. It can also accurately predict irregular demands, which has been difficult to do so until now, thereby reducing the safety stock.

2 Theoretical Background

2.1 Features of Intermittent Demand

The changing needs are sporadic and irregular in nature. Intermittent demand exists during the period when there is no demand, and thus identifying its period is impossible. In other words, the conventional researches that predicts the intermittent demand by analyzing only the amount of demand, results in a wide margin of error. However, the IoT technology can be used to collect and analyze information directly related to the life span of an individual product, thereby identifying the change in requirements of an individual product at a certain point in time. These products reflect the demand, and therefore, will be identified as the demand.

2.2 Current Method of Predicting Changing Need

Weibull distribution is the most widely used technique for predicting product failure. This method calculates the expected value of demand from the expected life span of products; therefore, it can be applied for calculating the overall changing needs. However, this method did not prove successful in predicting the sporadic changing needs [3]. Moreover, the time series analysis, used in the earlier research stages, did not fully reflect the sporadic nature of demand [3]. While other methods like exponential smoothing and bootstrapping have been proposed, they were limited to the collection of general information on the effective inventory level instead of demand prediction at specific times [3]. This paper suggests a new method for predicting the intermittent demand of a type of battery that is sensitive to changing needs, using IoT data for the measurement and collection of information, and artificial neural network to carry out the analysis and predictions.

2.3 Selection of Research Subject

Product failure can be divided into three major categories. The products that need to be changed for production are limited to “parts,” which are categorized into the following three groups.

Functional parts are those parts, which are changed following an accident, shock, or abrasion. These parts form the subject of this research. The other two groups are consumable parts that need to be changed periodically with time and accidental parts that are changed after the occurrence of accidents [4].

By using IoT technology, this research aims to collect real-time product status information, which keeps changing through abrasions, and analyze the accumulated data. Batteries were selected as the subject of research, as they are products that experience shortened life span due to usage. Therefore, this research aims to predict the changing needs of batteries by collecting their real-time status information and analyzing them.

2.4 Artificial Neural Network

An artificial neural network imitates the process of a human brain by delivering and processing information. Inside a human brain, there are innumerous neurons, which deliver and process information by transmitting weak electric signals to each other. When the total number of signals received by a neuron surpasses its maximum capacity, it enters an excited state (firing stage) and sends the electric signals to other neurons [5]. Artificial neural networks, which imitate this information delivering process using digital neurons, are widely recognized for their outstanding forecasting capability in non-linear relations, when compared to regression analysis [6]. The recurrent neural network model, which can arouse past memories through feedback coupling, is equipped with a system that is capable of self-studying, and can be adjusted to the changing environments. Since the late 1990s, the recurrent neural network model has been researched as a method for problem solving [6].

2.5 Recurrent Artificial Neural Network

The recurrent artificial neural network is a model that is appropriate for dealing with the concept of "time" [6]. As the results are saved on the network as feedback, it can remember the past and can be adapted to the changing environment. This network is classified into the following two types: Elman network and Jordan network.

The Jordan network is a model suitable for the control and learning of mobile robots. It analyzes the output information as input feedback in order to remember a robot's previous location.

The Elman network was developed to interpret the sentences in natural language, and it remembers the past by transforming the activated values of the hidden layer into input feedback. In other words, it remembers the threshold value of the hidden layer for a specific input, and when new information is inputted, it produces new results based on the past values.

In the Elman network, the hidden layers form a perfect circulated connection and include active neurons, whose states are determined by the neurons of the input and hidden layers [7].

In this research, the Elman network model was used to collect the real-time current data of the batteries and determine the next changing stage. By circulating only the accurate data, the network is able to remember the hidden layer threshold value for the next input.

3 Research Method

3.1 Measuring Battery Current

For this research, an IoT environment, which involved the real-time measurement of battery current, was set up. The current was measured in real-time using an NI (National Instrument) 9203 module, and the real-time data were collected using the Lab View program.

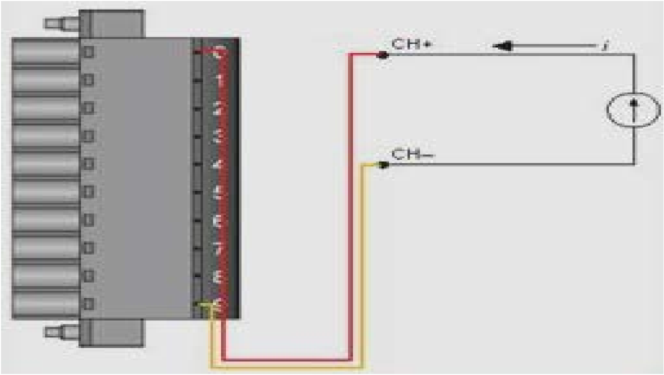
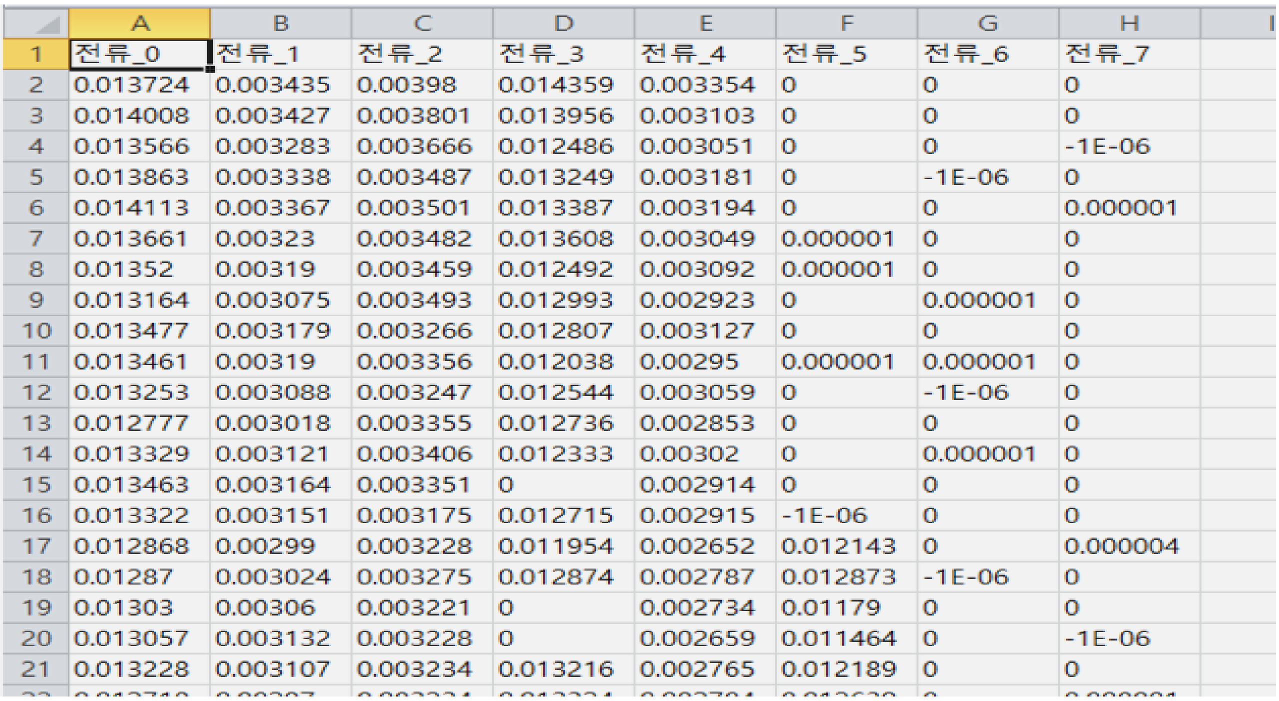


Fig. 1 NI 9203 Connection Diagram



	A	B	C	D	E	F	G	H
1	전류_0	전류_1	전류_2	전류_3	전류_4	전류_5	전류_6	전류_7
2	0.013724	0.003435	0.00398	0.014359	0.003354	0	0	0
3	0.014008	0.003427	0.003801	0.013956	0.003103	0	0	0
4	0.013566	0.003283	0.003666	0.012486	0.003051	0	0	-1E-06
5	0.013863	0.003338	0.003487	0.013249	0.003181	0	-1E-06	0
6	0.014113	0.003367	0.003501	0.013387	0.003194	0	0	0.000001
7	0.013661	0.00323	0.003482	0.013608	0.003049	0.000001	0	0
8	0.01352	0.00319	0.003459	0.012492	0.003092	0.000001	0	0
9	0.013164	0.003075	0.003493	0.012993	0.002923	0	0.000001	0
10	0.013477	0.003179	0.003266	0.012807	0.003127	0	0	0
11	0.013461	0.00319	0.003356	0.012038	0.00295	0.000001	0.000001	0
12	0.013253	0.003088	0.003247	0.012544	0.003059	0	-1E-06	0
13	0.012777	0.003018	0.003355	0.012736	0.002853	0	0	0
14	0.013329	0.003121	0.003406	0.012333	0.00302	0	0.000001	0
15	0.013463	0.003164	0.003351	0	0.002914	0	0	0
16	0.013322	0.003151	0.003175	0.012715	0.002915	-1E-06	0	0
17	0.012868	0.00299	0.003228	0.011954	0.002652	0.012143	0	0.000004
18	0.01287	0.003024	0.003275	0.012874	0.002787	0.012873	-1E-06	0
19	0.01303	0.00306	0.003221	0	0.002734	0.01179	0	0
20	0.013057	0.003132	0.003228	0	0.002659	0.011464	0	-1E-06
21	0.013228	0.003107	0.003234	0.013216	0.002765	0.012189	0	0

Fig. 2 Excel Spreadsheet

3.2 Artificial Neural Network-based Prediction Modeling

An artificial neural network model was established in order to predict the intermittent demand based on the analysis of the collected real-time current data. The artificial neural network model deducts specific values from the various input variables, and the information that is inputted as the activation function can be formulated by the following equation:

Sum of Inputs = $\sum_{i=1}^{n}(w_n\, x_n)$
n = Number of battery state information
x_n = nth state information of battery
w_n = Weight of nth state information

The sum of the input values is transformed into the output values by a non-linear function known as the activation function. When the final value obtained after subtracting the threshold value from the input sum is a positive number, it produces a binary output of 1. Alternatively, it produces an output of 0, when the final value is a negative number [5].

$$y_i = f\left(\sum_{k=1}^{n} x_{ki} w_{ki} - \theta\right)$$

y = Life exhausted (1 or 0)
θ = Threshold
f = Activation function
k = kth state information of ith battery

Therefore, "y" simultaneously shows whether a specific battery is nearing its time of change and the changing need. In short, the total sum of "y" can be shown as the overall changing need, "D."

$$D = \sum_{k=1}^{N} y_k$$

$$D = \sum_{k=1}^{N} f_k\left(\sum_{i=1}^{n} x_i w_i - \theta\right)$$

D = Total demand
N = Number of tires of which information has been obtained
f_k = Activation function of kth tire
n = Number of tire state information
x_i = ith tire state information
w_i = Weight of ith variable
θ = Threshold (tire life)

3.3 Building the Artificial Neural Network Model

From each line of the collected battery data, those with the same volt variable were extracted. They were then categorized into Volt and VoltF data. When the three types of data were constructed to establish the artificial neural network environment, the data categorized into Volt variables were sampled through the designation as different seed values of ind1 and ind2, in order to enable equal and random input of the data.

```
VoltT <- A1[A1$Volt == "TRUE",]
VoltF <- A1[A1$Volt == "FALSE",]
set.seed(1234)
ind1 <- sample(3, nrow(VoltT), replace=T, prob=c(0.5, 0.3, 0.2))
set.seed(4321)
ind2 <- sample(3, nrow(VoltF), replace=T, prob=c(0.5, 0.3, 0.2))

Volt.train <- rbind(VoltT[ind1==1,], VoltF[ind2 == 1,])
Volt.test <- rbind(VoltT[ind1==2,], VoltF[ind2==2,])
Volt.valid <- rbind(VoltT[ind1==3,], VoltF[ind2==3,])

Volt.train$Volt <- class.ind(Volt.train$Volt)
Volt.test$Volt <- class.ind(Volt.test$Volt)
Volt.valid$Volt <- class.ind(Volt.valid$Volt)

myformula <- Volt ~ .
```

Fig. Error! Bookmark not defined. Data Categorization

The finalized Volt.train, Volt.test, and Volt.valid data helped the learning process of the artificial neural network, and were established so that they could be used for the 1st test and verification. Moreover, the artificial neural network model was established to enable the analysis of other variables

```
test.err <- function(h.size, maxit0){
  Voltmodel1 <- nnet(myformula, data=Volt.train, size=h.size, decay=5e-4, trace=F, maxit=maxit0)
  y <- Volt.test$Volt
  p <- predict(Voltmodel1, Volt.test)
  err <- mean(y != p)
  c(h.size, err)}

out <- t(sapply(1:15, FUN = test.err, maxit0=100))
plot(out, type="b", xlim=c(0,15), ylim=c(0.9,1.05), xlab="The number of Hidden units", ylab="Test Error")
```

Fig. Error! Bookmark not defined. Deducting the Number of Hidden Layer

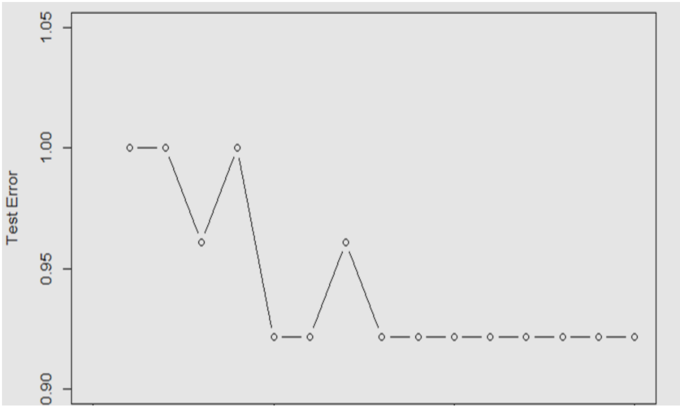


Fig. Error! Bookmark not defined. Hidden Layer Test Error Rate

The number of Hidden units

based on the Volt variable of myformula.

The test error rates for each number of the hidden layer were compared in order to define the number of nodes included in the hidden layer of the artificial neural network.

As shown in Fig. 5, the number of nodes was the lowest with the lowest test error rate when the number of hidden layers was 5.

4 Results

4.1 Artificial Neural Network Prediction Results

By designating the number of hidden layer nodes as 5 and educating the Vol.train data, the Volt.valid data was inputted to record the prediction values through the Volt.pred.valid variables of the artificial neural network.

```
model12 <- nnet(myformula, size=5, decay=5e-4, range=0.1, maxit=200, data=Volt.train)
summary(model12)

Volt.pred.valid <- predict(model12, new=Volt.valid)
```

Fig. Error! Bookmark not defined. Building Artificial Neural Network Model

The study evaluates the performance of the artificial neural network that was developed, based on the three performance factors, namely sensitivity, specificity, and accuracy. Sensitivity refers to the rate of accurate identification of the burned out batteries, specificity refers to the rate of accurate identification of the batteries that have not been burned out, and accuracy refers to the ratio of the accurate identification from the total prediction results.

Category		**Obs (Actual observation value)**	
		Remaining battery	**Used battery**
Pred (Predicted value)	**Remaining battery**	16	0
	Used battery	0	13
Sensitivity		1	
Specificity		1	
Accuracy		1	

Table 1 Classified Table of the Model (Valid Data)

Table 1 confirms that the established artificial neural network had a very high accuracy rate. When the network was evaluated based on the three performance indices, the accuracy was very high even when its sporadic nature was considered.

5 Conclusion

The method of predicting the intermittent changing needs through the IoT environment that is capable of collecting real-time information is expected to produce better prediction results than the conventional time-series measurement method. This research collects real-time information from individual batteries to determine when they should be changed. Based on this information, the research aims to predict the real-time demand. Therefore, from the perspective of general inventory management, eliciting the effective inventory level is not considered to have much difference from the conventional time series analysis prediction. However, it is expected to cause significant reduction in the demand test errors at specific points in time. In particular, the changing need is expected to show a high prediction rate, as it is based on the analyses of product status, rather than the probability. However, this method has limitations in that the IoT environment has not been established to the extent to conduct research by imitating an IoT environment and that there are no means to acquire product state information through wirelessly. In addition, the research did not consider the various variables due to limitations in the types of status information that could be collected. In conclusion, the follow-up research should predict demand using additional battery status information and enable adaptation to the changing environment through the circulation of the artificial neural network.

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