1. Introduction

With recent advancements, elevator controllers have various sensors to monitor the status of operating elevators for preventive maintenance. These elevator monitoring system designs can monitor the running status of the elevator and ensure the safety of the elevator. Marine elevators especially need the safety and maintenance monitoring capabilities due to the difficulty of maintenance at sea. An elevator company is planning to attach a device that collects error codes and other data about the operation of the elevator and sends them to the monitoring platform, which then analyzes the data using machine learning.

As a result, they are expecting to enhance the maintenance ability. We developed the marine safety monitoring system based on NMEA 2000 controllers and logging gateway. This system can handle the various sensor data and provide the diagnostic prediction information to the elevator controller. Adopted sensors include load cells, 9-axis IMU (Inertial Measurement Unit), wire rope clip, proximity, limit switch, etc. The logging gateway performs in-network sensor data processing because of the large volumes of raw data. The gateway can control the elevator controllers using the algorithms generated from various prediction model. Features for the prediction model have a very important role in the decision-making process. In addition to the prediction model based on the
big data on the server, subject matter experts’ decisions are needed in the process.

2. **System Design and Implementation**

2.1 **System Design**

The stakeholders such as ship owners and maintenance enterprises require marine elevator safety monitoring systems, which are able to:

- Collect status of all elevator operations and safety components
- Monitor the safety and operating status of the elevator remotely
- Analyze the status of the elevator and diagnose the error status in voyage
- Report the status of the elevator for easy maintenance during the ship’s arrival in port

Our monitoring system is designed to satisfy all of the above requirements shown in Figure 1.

![Figure 1. Overall System Configuration.](image1)

The monitoring system consists of a monitoring server, a logging gateway and controllers in the elevators which are connected with the NMEA 2000 logging gateway. The controllers consist of a main controller in machine room, a car controller in the cage and floor controllers in each floor. Server system software is designed using MEAN stack to easily implement and quickly deploy the system.

2.2 **System Implementation**

The NMEA 2000 logging gateway stores the sensor data locally, making safety status decisions by running the diagnosis prediction model trained in server. The gateway receives the broadcast messages through PGN, which contains control data of each controller and transforms them into the NMEA 0183-like messages. In-network processing module gathers the messages, pre-processes into events, and transmits them to the server and the diagnosis prediction model. They can be saved in the server to diagnose the events and send commands to controllers using PGN (NMEA 2000 messages). The engines of the diagnosis prediction model are algorithms coming from the server. The algorithms are trained model using big data collected from the elevator shown in Figure 2.

![Figure 2. Logging Gateway Structure.](image2)

3. **Prediction Model Performance**

3.1 **Test Environments**

We generated labeled data using an elevator simulation program and made four diagnosis prediction models: loads, slopes with roll and pitch, slopes with platform tilt, and elevator car operation status as shown in Table 1.

![Table 1. Features for Models](image3)
We labeled the roll and pitch slope data using the regulation in the DNV as shown in Table 2. The platform slope data is labeled when in stowed condition, which is when slope is 11.17° or above for a duration of 8.5 seconds or when slope is 23.66° or above.

### Table 2. Rules of Rolling and Pitching

| Classification | Rolling | Pitching |
|----------------|---------|----------|
| society        | Operation condition | Stowed condition | Operation condition | Stowed condition |
| DNV            | Angle   | ±10°     | ±22.5°    | ±5°     | ±7.5°    |
| Period         | 10 Second | -       | 7 Second  | -       |

#### 3.2 Test and Results

We simulated two test cases for each model. In the first test case, we used total load only and generated random car arrival time. In the second test case, we added total load feature of each load cells and total platform tilt feature to load model and roll and pitch slope model. Platform slope model was compared with and without roll and pitch slope. Operation status model used reasonable car arrival time to accept the normal within ±1 sec.

### 3.2.1 Load Prediction Model

We acquired the dataset with total load and each load of load cells. In the first two trials, we predicted the model using total load and sustained time, in the subsequent three trials, we used the previous trial features and each load cell's load features. The number of successes/failures and the ratio of accuracy and Kappa correlation are shown in Table 3.

### 3.2.2 Roll/Pitch Based Slope Prediction Model

We made the model using dataset with the sum of roll, the sum of pitch, and the time duration. The number of successes/failures and the ratio of accuracy and Kappa correlation are shown in Table 4.

### 3.2.3 Platform Based Slope Prediction Model

To get the labeled dataset of platform based slope

### Table 3. Load Prediction Model Test Results

| Trial | Dataset | Learning | Test | Fail | Success | Accuracy | $\hat{\kappa}$ | cf |
|-------|---------|----------|------|------|---------|----------|--------------|----|
| 1     | 7,475   | 5,980    | 1,495| 69   | 1,426   | 0.9538   | 0.9296       |    |
| 2     | 5,585   | 4,468    | 1,117| 54   | 1,063   | 0.9517   | 0.9260       |    |
| 3     | 10,480  | 8,385    | 2,095| 164  | 1,931   | 0.9217   | 0.8760       |    |
|       | 10,480  | 8,385    | 2,095| 1    | 2,094   | 0.9995   | 0.9992       | add local cells |
| 4     | 13,472  | 10,778   | 2,694| 188  | 2,506   | 0.9302   | 0.8900       |    |
| 5     | 15,709  | 12,568   | 3,141| 0    | 3,141   | 1.0000   | 1.0000       | add local cells |

### Table 4. Roll/Pitch Based Slope Prediction Model Test Results

| Trial | Dataset | Learning | Test | Fail | Success | Accuracy | $\hat{\kappa}$ | cf |
|-------|---------|----------|------|------|---------|----------|--------------|----|
| 1     | 3,370   | 2,696    | 674  | 5    | 669     | 0.9926   | 0.9886       |    |
| 2     | 2,560   | 2,048    | 512  | 3    | 509     | 0.9941   | 0.9910       |    |
| 3     | 4,745   | 3,796    | 949  | 1    | 948     | 0.9989   | 0.9984       |    |
| 4     | 6,186   | 4,950    | 1,236| 11   | 1,225   | 0.9911   | 0.9864       |    |
| 5     | 7,129   | 5,704    | 1,425| 7    | 1,418   | 0.9951   | 0.9925       |    |

### Table 5. Roll/Pitch+Platform Based Slope Prediction Model Test Results

| Trial | Dataset | Learning | Test | Fail | Success | Accuracy | $\hat{\kappa}$ | cf |
|-------|---------|----------|------|------|---------|----------|--------------|----|
| 3     | 4,745   | 3,796    | 949  | 0    | 949     | 1.0000   | 1.0000       |    |
| 4     | 6,186   | 4,950    | 1,236| 0    | 1,236   | 1.0000   | 1.0000       |    |
| 5     | 7,129   | 5,704    | 1,425| 1    | 1,424   | 0.9993   | 0.9989       |    |
prediction model, we set the simulated environment to the DNV guideline. We use the platform tilt feature which is obtained from Figure 3.

```c
fpitch = pitch * 90.0 / 4096.0;
frroll = roll * 180.0 / 4096.0;
platform_tilt = cos(fpitch * PI / 180.0) * cos(froll * PI / 180.0);
if (platform_tilt > 1.0) platform_tilt = 1.0;
if (platform_tilt < -1.0) platform_tilt = -1.0;
platform_tilt = acos(platform_tilt) * 180 / PI;
```

**Figure 3.** Platform Tilt Calculation Method.

Table 6 shows that in the first two trials, average roll and pitch values are used and in the following three trials, weighed roll and pitch values are used, which are 8.83° or above during 7 seconds and 23.66° and over.

Table 7, the test results are obtained from labeled data using platform tilt feature, summed roll feature, summed pitch feature, and sustained time feature in platform tilt event messages.

### 3.2.4 Car Operation Status Prediction Model

We assumed that motor speed is 60m/minute and height of one floor is 2m because the elevator inverter controls the motor speed. In the first two trials, we labeled data as a “success” when the car arrived in time and in the following three trials we labeled data as a “success” when car arrival time is in ±1 second margin as shown Table 8.

### 3.3 Analysis of the Results

The analysis results were recorded using 80% random sampling of labeled event message data sets for machine learning which were generated in cars and collected automatically in the server, and the remaining 20% from the input of the learned prediction model. Evaluation method was decided out of accuracy and the Kappa correlation coefficient. After the analysis, we determined that additional features enhanced accuracies in every model. In the operation status model case, the accuracy is enhanced, but the Kappa correlation coefficients are dropped.

#### 3.3.1 Load Prediction Model

Figure 4 using total load features and total holding time features, accuracy to determine whether event messages are normal, overload and biased load is between 0.92 and
0.95, Kappa correlation coefficient is considerably high between 0.88 and 0.92.

Figure 4. Accuracy and Kappa of Load Prediction Model.

As shown in Figure 5, we test with above features, by adding total loads feature for 4 load cells, resulting in accuracy and Kappa correlation coefficient of close to 1.00.

Figure 5. Accuracy and Kappa of Load Prediction Model with load cell features.

3.3.2 Roll/Pitch Based Slope Prediction Model

The prediction model which has 99% or above of accuracy and Kappa correlation coefficient, can predict the status of cars, whether it is normal, immediate stow or waiting stow, using total roll values, total pitch value and status holding time features as shown in Figure 6.

Adding total platform weight features to total roll values, total pitch value and status holding time features, the prediction model’s accuracy and Kappa correlation coefficient were close to 1.00. Therefore, in the case of roll & pitch slopes and platform slopes, it could have 0.99 or above of accuracy, without adding platform slope related features as shown in Figure 7.

Figure 6. Accuracy and Kappa of Roll/Pitch based slope prediction model.

Figure 7. Accuracy and Kappa of Roll/Pitch Based Slope Prediction Model with Platform Tilt Features.

3.3.3 Platform Based Slope Prediction Model

Using platform slopes which is unified roll and pitch features, it shows the accuracy of 0.98 in the case of platform slopes by weighted slope and time, while the accuracy is 0.91 in the case of platform slopes by average slope and time.

Figure 8. Accuracy and Kappa of Platform Based Slope Prediction Model.
3.3.4 Car Operation Status Prediction Model

Car operation status prediction model measures whether car operation is normal or not, with floor movement pitch and arrival time pitch. In the case of calculating accurately without tolerance for arrival time pitch, it shows accuracy of 0.95 ~ 0.96. On the other hand, Kappa correlation coefficient is only 0.81 for decision.

However, deciding the results with tolerance of ± 1 second, it shows accuracy of 0.97 and almost completes consistency with the Kappa correlation coefficient of 0.86 or above.

4. Conclusion

We designed and implemented a safety elevator monitoring system based on the NMEA 2000 network. The logging gateway provides diagnosis prediction model trained by big data on the server for the marine elevator maintenance.

With analyzing the results of the above 7 tests, we can conclude the followings:

- Among the elevator car operation status models, Kappa correlation coefficient is 0.81 or above for overall prediction models except for the case of accurate arrival time as evaluation criteria, which is considered completely consistent.
- Loads model should include total weight feature for 4 load cells to decide accurately.
- Role & Pitch Slopes model and Platform Slopes model can secure accuracy 0.99 over above, without using a separate single platform slope.

Therefore, we conclude that it is possible to generate the prediction model with satisfactory accuracy without using complex deep learning algorithms, such as RNN (Recurrent Neural Network) etc., in order to sample features.

5. References

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