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Neural Network Models to Anticipate Failures of Airport Ground Transportation Vehicle Doors

Alice E. Smith, David W. Coit, and Yun-Chia Liang

***Abstract*—This paper describes a case study of the development and testing of a prototype system to support condition-based maintenance of the door systems of airport transportation vehicles. Every door open/close cycle produces a "signature" that can indicate the current degradation level of the door system. A combined statistical and neural network approach was used. Time, electrical current and voltage signals from the open/close cycles are processed in real-time to estimate, using the neural network, the condition of the door set relative to maintenance needs. Data collection hardware for the vehicle was designed, developed and tested to monitor door characteristics to quickly predict degraded performance, and to anticipate failures. The prototype system was installed on vehicle door sets at the Pittsburgh International Airport and tested for several months under actual operating conditions.**

***Note to Practitioners*—This paper describes the development of an automated system that consists of hardware and software to monitor the condition of a mechanical door set on board airport ground transportation vehicles. The aim is to use the current and past conditions to estimate (using neural network predictions) when the door set is in need of scheduled maintenance. This will allow airports to achieve very high availability rates (near 100%) for these vehicles, while also achieving cost effective maintenance policies. Currently, vehicles tend to be over-maintained because of the availability levels mandated by airport authorities. This system, although in prototype form, shows the viability of an automated condition-based maintenance approach. The drawback proved to be the variability among door sets from vehicle to vehicle, which means the predictive software of the system would need to be customized for each vehicle. Several patents, both U.S. and foreign, have been granted to this automated system.**

***Index Terms*—Condition monitoring, neural network, predictive maintenance, preventive maintenance, transportation.**

I. INTRODUCTION

The ground transportation people mover vehicles that are found in most major airports in the world have stringent availability and safety demands. Although they operate over short, fixed routes, they are subject to nearly constant use, sometimes under adverse outdoor environments, with frequent stops and a large volume of passengers. A leading manufacturer of these vehicles cooperating with universities developed and tested a prototype system utilizing a condition-based

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maintenance approach for improving the operational reliability and availability of the vehicle doors. Doors were monitored in real-time with respect to their current operational state and predictive maintenance planning models were developed based on the trends identified.

Door failures or unacceptable degradation levels may force the vehicle to be temporarily shut down due to safety concerns. Because of passengers holding the doors open, numerous open/close cycles and harsh weather conditions, the door's components are subject to stress and deterioration; thereby creating a unique door closure signature or profile prior to actual failure. Deterioration in either the electrical DC motor that controls the operation of the door or the mechanical levers, rollers, tracks, or switches can cause failures. In airports, labor-intensive preventive maintenance programs are currently used to ensure adequate availability. This scheduled maintenance approach requires experienced personnel to determine the cause(s) of problems and can result in components being serviced even though there is no immediate need for maintenance.

The initial condition-based maintenance approach by the manufacturer was an analytic model of door degradation and failure based on a physical description of the door system components and their interactions. When comparing the analytic physics-of-failure model outputs with those obtained from a test vehicle, it was found that the model was significantly deficient. Therefore, an empirical data synthesis approach was adopted to process the signals from the people mover, to identify meaningful trends within available data, and to estimate when maintenance should be performed. Neural networks were used as the primary predictive modeling tool.

Significant research has been conducted on condition monitoring and integrated prognostics. These include research by El-Wardany *et al.* [1], Szecsi [2], Wang and Christer [3] and Bunks *et al.* [4], Yam *et al.* [5], Lu *et al.* [6], Greitzer *et al.* [7], Roemer and Kacprzynski [8], and Yan and Lee [9]. Reviews of condition-based maintenance include Dimla, Jr. *et al.* [10], Jardine *et al.* [11], and Djurdjanovic *et al.* [12]. Neural networks have effectively been used in other applications to detect trends within complex data sets and to predict performance degradation of operating systems in real-time. Specifically, neural networks have been effective in anticipating failure for cutting tools [13]–[15] and machinery [16], [17]. Additionally, there have been other applications including mining [18], hydroelectric power plants [19] and component placement for surface mount technology [20]. A preliminary version of the project described herein is contained in [21].

II. Door System and Data Acquisition

The vehicle doors operate as an open-loop system receiving signals from an automatic control system that initiates action of the motor. The motor turns an operator arm, which runs along a guidance slot in the door (see Fig. 1). The movement of the operator arm pulls or pushes the door to the open and closed positions. The door is equipped with rollers that ride in a track at the top of the vehicle and there is a track at the bottom of the vehicle in which the door rides. As the door goes through its cycle, microswitches connect and disconnect resistors in the electrical circuitry, which change the speed of the moving door. A door typically opens in 3–3.5 s, and closes in 4–4.5 s, and is quite similar to doors found in elevators.

A. Data Collection

An experimental setup was made to gather data using a test vehicle provided by the industrial partner at their test track. Although it would have been useful to monitor some operating people movers in the field, there were practical restrictions that prevented this type of data collection. First, because of the public nature of airports, any alteration to a vehicle, even in the form of passive monitoring, is difficult to get

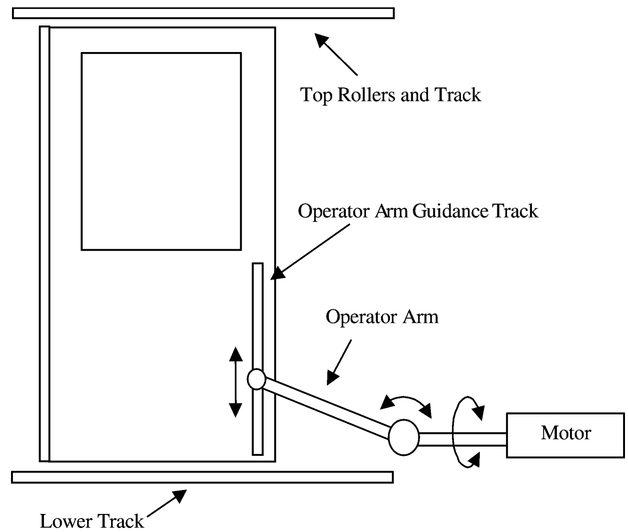

Fig. 1. Typical airport transportation vehicle door.

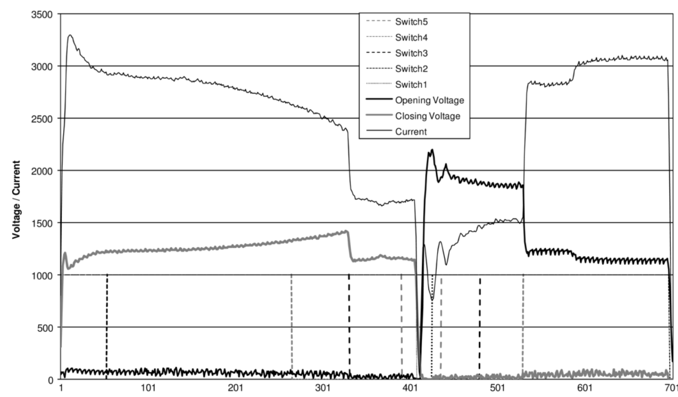

Fig. 2. Typical signals over a close and open cycle from one door set.

approved. Second, passive data collection from fielded systems may involve lengthy data collection intervals without significant degradation.

The key measurable data collected are: a) current through the motor (amps); b) voltage across the motor (volts); c) time interval of the open and close cycle (to the 0.01 s); and d) timing of the microswitches (to the 0.01 s). All signals pass through a circuit board that contains voltage dividers that scale down the voltage, and filters for the current measurements and motor voltage. The circuit board sends the signals to a built-in A/D converter, which in turn, sends them to an on-board laptop computer. Data collection software was designed to collect data when both the closing voltage and the opening voltage are not equal to zero, i.e., data was only collected when the door system was in operation.

The energy in joules required to move the door between two positions is given by

$$\mathrm{Energy} = I \times |c_1 \times V_C - c_2 \times V_D| \times c_3 \times T \tag{1}$$

where

$$I = \frac{c_3 \times V_{\mathrm{sg}}}{c_4 \times c_5}. \tag{2}$$

I denotes the current (V_{sg} is the voltage shunt to ground), V_C and V_D represent closing voltage and opening voltage, respectively, and T denotes the time between two samples. In these equations, c_1, c_2, c_3, c_4, and c_5 are conversion constants determined by a circuit board designer.

Fig. 2 shows a typical set of signals over a single open and close cycle. In the figure, the voltage and current are continuous, while the switch signals (dashed vertical lines) occur only when the door passes

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a switch. Switches are numbered 1 through 5 and occur sequentially while opening (right side of the figure) and in reverse sequence while closing (left side of the figure).

The data acquisition module has encoder inputs, isolated digital inputs, voltage inputs, a temperature input, and current sensing inputs. Five digital inputs are used to read the door switch contacts to determine the door position relative to time. Two voltage inputs measure the voltage on each side of the motor's armature. Three current sensing inputs measure the current through the motor by subtracting current through either the open or closed resistor circuit from the total current. The temperature input was designed to compensate for temperature differences that would cause accuracy of the measuring system to change.

B. Friction Degradation Data

As the vehicle operates, degradation can occur caused by weather conditions, foreign substances in the path of the door, passengers holding the door open, and other events. This can result in the following failure modes: door failure to close, worn out overhead rollers, bent operator arm, and worn out operator arm track. All of these increase the frictional resistance against the door, causing the motor to work harder. Therefore, the effect of friction on the door is the most important diagnostic parameter for the vehicle door system. Note that this system is not designed to anticipate catastrophic failures.

To produce frictional forces on the door which simulate aging, a device was designed, built and installed onto one of the doors of the test track vehicle. Four levels of forces were applied to the device (2, 4, 6, and 8 lbs) and these forces were first applied (and then maintained) at three different horizontal locations (after the door has traveled approximately 0, $1/3$, and $2/3$ through its cycle). The full combination of these two factors results in twelve different experiments. Each experiment was run for ten close-open cycles. Also, ten cycles of normal operation were collected to establish a baseline.

A continuous and dimensionless degradation measure was defined ranging from 0 to 1 representing conditions of no degradation to full degradation. The most extreme force (8 lbs) results in door failure (failure to open or close), and is thus, assigned a rating of 1. Other degradation measures were linear in comparison to the maximum level. Note that degradation is measured by energy used by the door set to open or close, and is affected by the amount and location of the friction force to be overcome. A linear degradation measure was used in the absence of data or physical models to support a more complicated measure and because many nonlinear relationships exhibit linear forms when viewed in a smaller period of time.

C. Data Preprocessing

Data were simulated to fill in the gaps between the physical experimentation that was described in Section II-B. The simulation involved a computer linear degradation model with added Gaussian noise ("white noise"). This was done to create the pattern of continuous degradation from healthy to fully degraded. A plot of the combined actual and simulated energy data is shown in Fig. 3. Holt's method of exponential smoothing [22] was used as a low pass filter to reduce the noise in the data and more readily detect the degradation trend.

Fig. 3 provides an example of energy data in joules showing operation of the door from fully functioning to fully degraded (door set is fully functioning until about data point 200). The top line of each set of three is for the force being applied the entire length of the door track, the middle line is for the force being applied for $2/3$ the length of the door track and the bottom line is the force being applied for $1/3$ the length of the door track. Data is a mixture of physical experimentation interspersed with simulation.

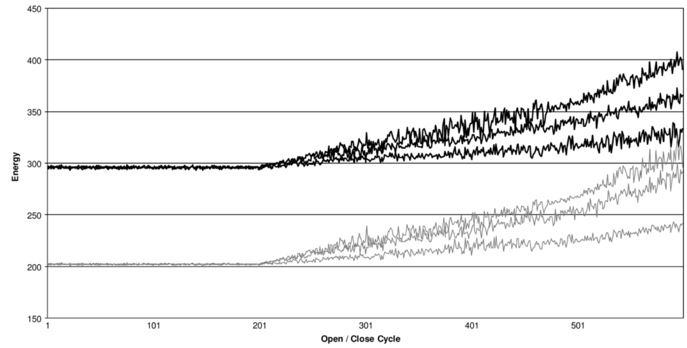

Fig. 3. Energy data during door operation—dark is closing energy and light is opening energy.

III. Reliability Assessment Based on Observed and Projected Degradation Paths

Using the data from Section II, a method to trigger maintenance of a door set can be devised. Consider $z(\mathbf{x}(t))$ to be the dimensionless degradation measure as a function of door closure inputs, $\mathbf{x}(t)$, observed at open/close cycle t. Consider the failure threshold to be D, and δ is a degradation measure ($\delta < D$) that is indicative of unacceptable degradation, yet observed prior to actual failure. A reactive, but preventive task can be initiated at this observation ($z(\mathbf{x}(t)) \geq \delta$). Then, system failure can be prevented as long as the degradation-level does not deteriorate to the D level before the first available time for maintenance, i.e., between 2 a.m. and 4 a.m. for airport vehicles. In practice, the degradation characterized by this system is lengthy and steady (increasing frictional force) so that predicting δ one time step ahead is sufficient to schedule maintenance well in advance of reaching threshold D.

Planned maintenance can also be implemented by projecting observed trends to predict a lower-bound value for time-to-failure. The projected failure times are determined individually for each door assembly based on the observed model inputs and predicted output. A lower-bound on time-to-failure is made based on the predicted mean failure time and a numerical adjustment.

IV. Neural Network Model Development for Condition Monitoring

A. Choice of Neural Network Paradigm

Different neural network paradigms and architectures were tested and compared based on their ability to relate door closure data to impending failure. Because of its commonly available software and its theoretical property of universal approximation [24], [25], a backpropagation network was chosen as one neural network paradigm to study. Two other neural network paradigms were also studied which are easily reproduced in software, have universal approximation capability but also reduce dependence on architecture selection. These are the cascade correlation network, which builds its own architecture incrementally, also using an error feedback algorithm to minimize squared error, and the radial basis function network, which uses basis functions (hyperbolic tangent in this case) to localize inputs prior to using the error feedback minimization algorithm to determine output layout weights. These alternative paradigms offer the distinct benefit that a specific model architecture does not have to be preselected.

B. Model Refinement and Training

Two sets of input variables were considered in each neural network:

1) four input variables (closing energy, opening energy, closing time, and opening time);

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TABLE I
RESULTS OF THE BEST NETWORK FOR THE DIFFERENT NEURAL NETWORK PARADIGMS FOR THE FOUR INPUT CASE

Network	Training RMS	Training R^2	Testing RMS	Testing R^2	Number of hidden neurons in the network
Backpropagation	.101	.968	.073	.985	5
Cascade Correlation	.050	.978	.071	.955	16
Radial Basis Function	.035	.989	.100	.917	15

RMS is root mean squared error.
R^2 is the coefficient of determination.

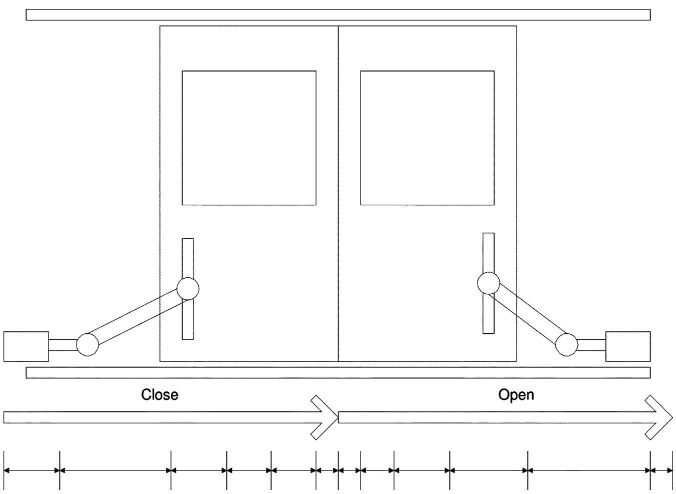

Fig. 4. Segmentation of track into six segments by the five switches.

2) 24 input variables (closing energy, opening energy, closing time, and opening time over the five-switch locations, creating six physical longitudinal door sections as per Fig. 4).

Time was in units of seconds, while energy was in units of joules. One output variable, the level of degradation, was a continuous unitless value between 0 and 1, where 0 is perfectly healthy and 1 is fully degraded. The extremes of this scale were verified physically on the test vehicle door set. Between the extremes, a linear degradation form was assumed. This characterization of degradation between these values is nonspecific. In practice, a threshold needs to be defined to initiate preventive maintenance, and for airport ground vehicles, this would be done conservatively. Data was obtained from physical experimentation on a test vehicle augmented by simulation and exponentially smoothed, as described in Section II. This data had a period of 600 open/close cycles from healthy to full degradation. Recall that the neural network predicts only one time step ahead based on the previous time step's values. Therefore, the period of degradation is not relevant to the prediction training or ability of the neural network. While one time step might be inadequate for some applications, for the degradation of the door set, change takes place slowly and steadily. Therefore, the degradation value does not alter drastically from one time step to another.

Table I shows results of the four input case for the best networks of each paradigm. While the radial basis function network achieved the lowest error on the training set, its ability to generalize was weak, as evidenced by the large testing error rate. The R^2 (coefficient of determination) values of all networks were high, however, indicating that neural network predictive modeling is effective for this application. Table II shows the results of 24 input case for the best networks of each paradigm. Here, the backpropagation network was superior for

TABLE II
RESULTS OF THE BEST NETWORK FOR THE DIFFERENT NEURAL NETWORK PARADIGMS FOR THE 24 INPUT CASE

Network	Training RMS	Testing RMS	Number of hidden neurons
Backpropagation	0.00674	0.04419	25
Cascade Correlation	0.04144	0.08430	50*
Radial Basis Function	0.04662	0.10998	20

RMS is root mean squared error.
* 50 was set as an upper bound.

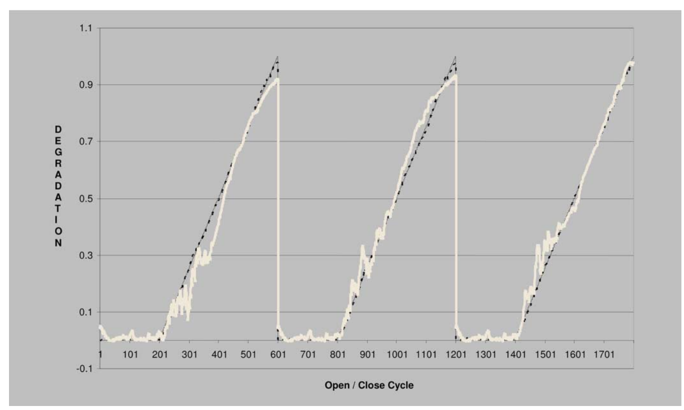

Fig. 5. Actual (target), training and testing data for a backpropagation network with 25 hidden neurons and a learning rate of 0.3 over three degradation cycles. Actual and training data trace the same dark line, while testing appears as the white line.

both training and testing. This network is also significantly more accurate than the four input case. Therefore, it can be concluded that dividing the energy and time into physical increments along the door track is helpful in estimating door condition. Fig. 5 shows typical predicted (both training and testing) versus actual over three degradation cycles using the backpropagation, 24 input trained neural network. It is difficult to discern but the training and target lines are virtually identical. The linear form is in keeping with degradation being caused by steadily worsening conditions rather than catastrophic failure or intermittent causes.

V. FIELD TEST AT PITTSBURGH INTERNATIONAL AIRPORT

The next phase of the project was to install the prototype system at the Pittsburgh, Pennsylvania International Airport Site for a three-month period. Eight units were installed in the landside car on the south train.[1] After installation, all doors were tested to assure that safety or operation was not compromised.

[1]At the Pittsburgh airport, there are two indoor "must ride" vehicles, one on the south side and one on the north side. Both move back and forth from the landside terminal to a single transport terminal.

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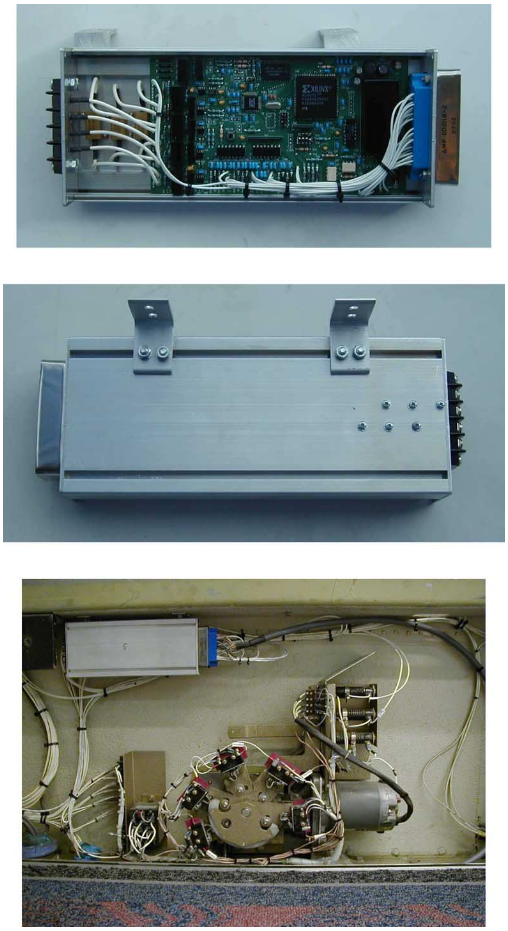

Fig. 6. Prototype system installed on a vehicle at the Pittsburgh International Airport.

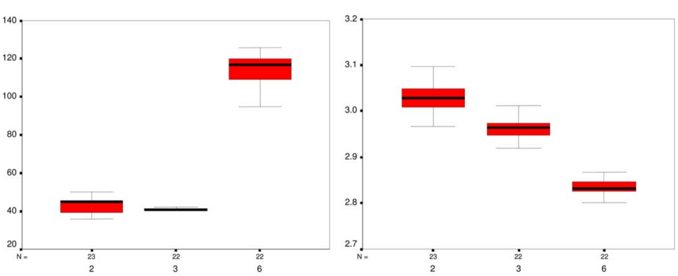

Fig. 7. Box plots of mean open energy in joules (left) and mean close time in seconds (right) of three door sets during the trial.

Fig. 6 shows the prototype installed into the control circuit of one of the doors of the Pittsburgh International Airport vehicle. Two harnesses were required for installation—one for the digital signals, communication and voltage signals and a second harness of a thicker gauge wire for the current connections. If any failure occurred within the prototype data acquisition unit itself, it could quickly be disconnected from the system. This aspect was critical for obtaining approval for a live field test as airports are within the public domain and passenger safety and vehicle availability are paramount.

Fig. 7 shows example data from the field trial as a box plot where the box encloses the middle half of the distribution (25th percentile to 75th percentile, also called the interquartile range) with the median value denoted as a line across the box. The extending

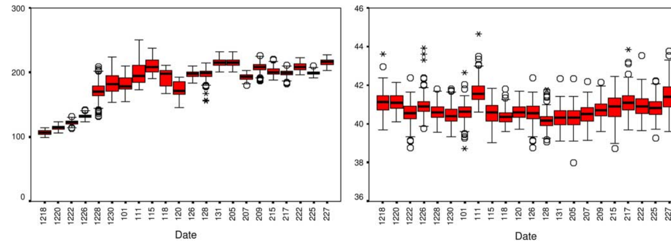

Fig. 8. Box plots of mean close energy of a door set exhibiting degradation over time (left) and of a stable door set (right). (Circles and stars are individual outlying observations.)

lines from each box (the "whiskers") go to the largest and smallest observations not deemed outliers. There are three door sets which, although all initially healthy, exhibit different operating characteristics. It is evident that inherent differences exist among the signal (energy and time) traces of the vehicles' door sets (note also the significant energy differences from the test track vehicle used in the development work—this highlights the individual differences among airports—different door and vehicle models as well as different operating conditions). This motivates the need to customize the predictive algorithm to each door set. This could be accomplished by gathering data passively during a specified period when the system is first installed in a vehicle, assuming the door is healthy when installed. Once the normal behavior and profiles of each door set are known, the algorithm could be adjusted to correctly predict condition for that door set. Should energy start to exhibit an upwards trend (see Fig. 8 on left), preventive maintenance would be triggered. Once a door system was maintained, its energy tracings should return to previous healthy levels. Besides individual door differences, the location of the vehicles in the different airports will affect the typical door signal signatures. For example, in Frankfurt, Germany, the vehicles operate outside in a relatively harsh environment. The same is true in Tampa, Florida, except the climate conditions are vastly different and include effects of humidity and salt.

The field trial data indicated that energy is a better indicator of door health than time. The data also showed that time and energy were not well correlated for individual door sets. This is contrary to expectations. It is postulated that this occurs because open and close times are largely affected by riders in the vehicle (leaning against the door or attempting to hold a door, for example), while energy used to open and close the doors primarily relates to the condition of the track along which the door moves. Fig. 8 on the left shows a standard box plot of a door set with its closing energy tracings over about $2(1/2)$ months (over various days during the field trial). These plots are by date (x axis) with the observations during each day summarized as a box plot (y axis). This door set shows degradation from the beginning of the trial through the end, although the increase in energy is nonlinear. Similarly, in a door set not exhibiting degradation, the energy traces are shown on the right.

VI. Conclusion

The following conclusions from the data collection, analysis, modeling, and field test can be made.

- It is possible to design, build, and implement a data predictive maintenance system for airport vehicle doors without major vehicle design changes.
- Monitoring door operation appears to be practical and effective; a supervised neural network approach, such as backpropagation, preceded by exponential smoothing works for prediction of

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door degradation. While the method herein used smoothing designed for a linear system, another smoothing method could be employed if needed. Additionally, many nonlinear systems when viewed in smaller time slices exhibit roughly linear behavior. The prediction was one time step ahead in this application, however, a neural network could be readily trained to predict multiple time steps ahead. This would provide more time to schedule maintenance but would likely reduce the accuracy of the prediction.

- Significantly more data from doors in some known state of degradation is needed in order to build effective predictive models that are accurate over the entire operating range of door states.
- Vehicle doors do exhibit a wide variety of "normal" behavior and therefore predictive models will need to be empirically customized to individual airports, vehicle systems and, in this case, individual door sets. Using on line learning would certainly facilitate the development of customized models.

A U.S. patent and several Asian and European patents have been granted for this system.

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