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Movement identification model of a steel structure based on structural health monitoring system

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ABSTRACT

This study presents a steel container crane movement analysis and assessment based on structural health monitoring (SHM). The accelerometers are used to monitor the dynamic crane behavior and a 3-D finite element model was designed to express the static displacement of the crane under the different load cases. The multi-input single-output nonlinear autoregressive neural network with external input (NNARX) model is used to identify the crane dynamic displacements. The analysis results indicate that: (1) the mean relative dynamic displacement can reveal the relative static movement of structures under environmental loads cases; (2) the environmental load conditions clearly affect the crane deformations in different load cases; (3) the crane deformations are shown within the safe limits under different loads.

1. INTRODUCTION

The steel container crane structure is the key equipment of the harbor handling operation in the harbor. Under the effect of long-term impact loads, the mechanical conditions of the container crane will appear many failures, such as the running failure of the slewing bearing, crack and deformation of the metal structure and others, which posses a grave threat for the safety of devices and operators (Richard et al. 2001; Zhiping et al. 2011; Ding et al. 2012). Environmental and operational variations, such as varying temperature, moisture, and loading conditions affecting the dynamic response of the structures cannot be overlooked either (Sohn et al. 2004). In fact, these changes can often mask subtler structural changes caused by damage. The process of implementing a movement and damage identification strategy for civil and mechanical engineering infrastructure is referred to Structural Health Monitoring (SHM) (Sohn et al. 2004; Kaloop 2012). By SHM of container cranes, the deterioration tendency of metal structure can be predicted and sudden accidents may be avoided.

The finite element model (FEM) analysis is often carried out to assist structure

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design and limited real analysis. Therefore, the real loading conditions were always much more complicated than the modelers can imagine. Li et al. (2006) refer to that the structural response under effecting loads were consists mainly on three components: static, quasi-static and dynamic components. The accelerometer sensor is one of sensors which used to measure the dynamic component of structures, whereas it can be detected relative higher vibration of structures (Meng et al. 2007). In addition, the accelerometer is able to extract acceleration response of a structure with natural frequency up to 1,000 Hz because of the high sampling frequency (Chan et al. 2006).

The cranes health monitoring analysis studies are less than other studies of the different structures; refer to (Deng and Xu 2009; Bhimani and Soaderberg 2010; Zhiping et al. 2011; Ding et al. 2012). The cost of SHM system is considered one of important issues for the safety design for the crane structure. For this reasons, using only one type of sensors to monitor the crane deformations is considered very complicated to extract the crane full periodic and identification movement models. However, this paper focuses on the analysis of the Pusan port container crane based on accelerometer measurements under environmental conditions loads and considering the container-moving load. Then using the FEM analysis and the identification model to study the safety and the vibration state of the crane in both time and frequency domains. Finally, assessing the crane behavior using the SHM system based on FEM and results have been concluded.

2. CRANE DESCRIPTION AND SHM SYSTEM DESIGN

Container cranes are the typical portal structures which directly exposed to the typhoon, tsunami and earthquake. Especially, Pusan ports are somewhat expected to be damaged by typhoons every year, and have experience of crane collapses in 2003 (Fig. 1). The crane condition diagnosis by SHM can give some useful preparation to natural disaster.

Fig. 1 Crane collapse by Typhoon in Pusan ports (Gamman, Jasungdae, 2003)

In this study, real time monitoring system was built at a container crane located in Pusan Newport. Target crane is made by ZPMC, which has 74 m height and 1,680 Ton weight. This model is most widely introduced and used in Korea, and which has representative nationally. Preliminary simulation gave the measuring points for the accelerations monitoring (Fig. 2). Totally seven acceleration sensors were installed based on the FEM results.

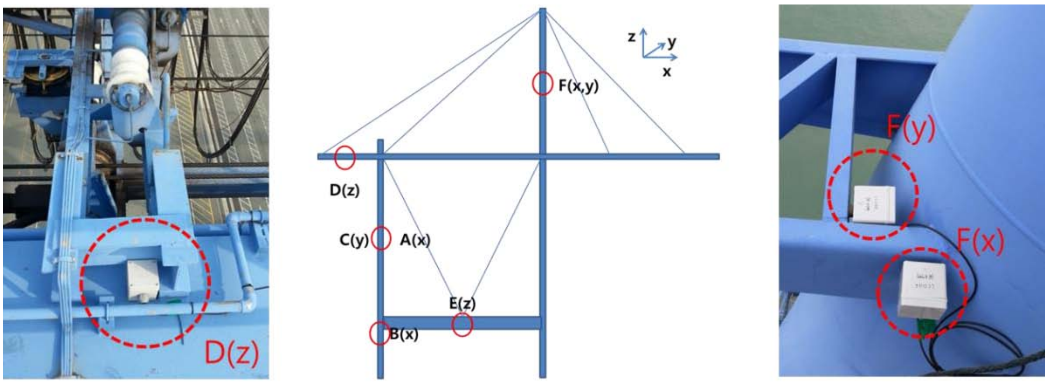


Fig. 2 Accelerometer locations and acceleration recording axes

SHM system is composed as Fig. 3. Sensors are connected to a data acquisition device by wire. Measured data are digitized in AD converter and delivered through Bluetooth module and Access Point (AP) by wireless. Data collected are stored in SD memory and PC. A data acquisition device used in this research has one channel; each device was time synchronized by signal sender from PC each time. PC stores data in real time and controls the sensor nodes (data acquisition devices) (Table 2).

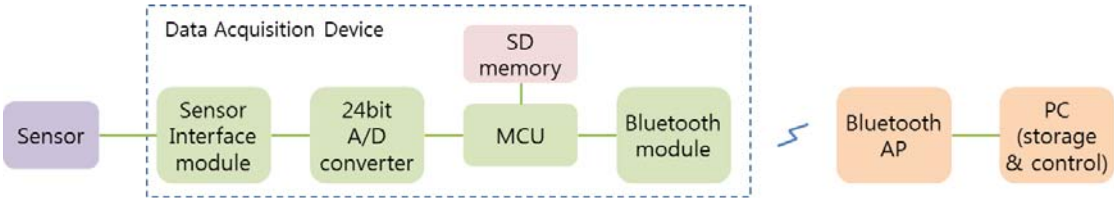


Fig. 3 Structural Health Monitoring system composition

As a result of feasibility measurement, acceleration range of crane structure is about maximum 3g. Therefore, sensors were set which have the amplitude of 5g (Table 1 and Fig. 4). DAQ modules are prepared to measure the accelerations of each points of container crane. All devices are set inside the housing to protect against wind and rain (Fig. 5). The electric power was supplied from the crane machine room.

Table 1: Acceleration sensor performance

Parameter	Description
Sensitivity (@160Hz)	10.046V/g
Amplitude	5g pk
Resolution	0.000002g rms
Transverse Sensitivity	3.9%
Frequency Range	0.1-300Hz (±10%)
Resonance Frequency	1.2kHz
Amplitude Linearity	<1%

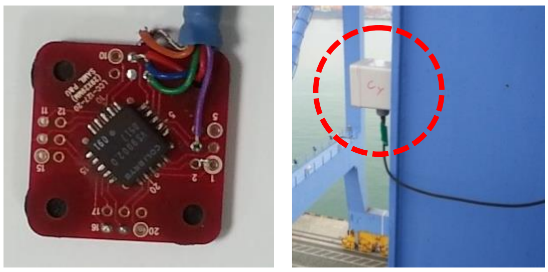


Fig. 4 Acceleration sensor photo, and in-situ installation at measuring point

Table 2: Data-logger performance

Parameter	Description
Programmable Offset	~±5V
Transmit Frequency	2.0GHz Bluetooth
Sampling Rate	1~1000Hz
Synchronized Accuracy	10ms
Resolution	16bit
Size	80×80×32(mm)
Power saving	Wake/sleep
Data backup	Storage PC installed

Fig. 5 Experimental setting of data-loggers and storage PC

3. METHODOLOGY

3.1 FEM Design and load system

The Pusan crane is modeled using the SAP2000 software considering the dead load of the different steel members, the environmental conditions and the container-moving load (Fig. 6). The analyzed carne is a steel container crane that lifts objects by a hoist, which is fitted in a hoist trolley and move horizontally on pair of rails fitted under a beam.

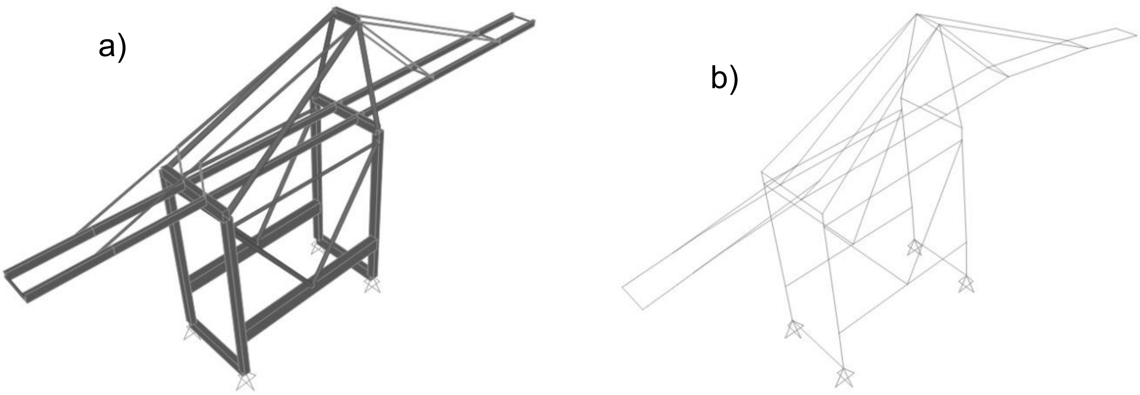


Fig. 6 a) Crane finite element model and b) mode shape using SAP2000

The crane consists of two main parts: the base and the moving load rail arm. The base width and depth are 42.67m and 20.60m, respectively. The second part is the moving load arm with total length 153.60m. During our experiments, both the container-moving load and environmental condition excited the crane. The moving load is a container with weight 65 Ton moving horizontally for a distance 127.67m along the crane arm with speed 1m/sec on the main hoist. The FEM modal frequencies for the first five modes of the crane are 0.09; 0.398; 0.561; 0.657 and 0.659 Hz, respectively.

3.2 Identification model

In most practical applications, the system is not known and has to be estimated from the available information that is called the identification problem. Three main choices in system identification are data, model class and criterion. In addition, system identification often involves several runs of the empirical cycle that consists of the specification of the problem, the estimation of a model by optimization of the criterion, the validation of the resulting model, and possible adjustments that may follow from this validation. The method, which is used, is the multi input single output (MISO) NNARX. In general; ARX structure (Norgaard 2000; Zhiping et al. 2011) uses delayed inputs and outputs in order to determine a prediction of the out-put at one (or more) sample interval(s) in the future. The most used model structure is the simple linear difference equation:

$$y(t) + a_1 y(t-1) + \cdots . + a_{na} y(t-na) = b_1 u(t-nk) + \cdots . + b_{nb} u(t-nk-nb+1) \quad (1)$$

Which relates the current output *y(t)* to a finite number of past outputs *y(t-k)* and inputs *u(t-k)*. The structure is thus entirely defined by the three integers na, nb, and nk. Where, na is equal to the number of poles and nb-1 is the number of zeros, while nk is the pure time-delay in the system. Parameter estimation of the linear ARX models is followed by a standard minimization of the sum squared errors approach (Norgaard 2000). In the absence of noise, the model could be determined directly from linear algebra from very few data points, in a relatively trivial manner. In the ARX structures, it is assumed that the noise is equivalent to pre-filtered white noise where the poles of the filter are identical to those of the resulting ARX model. Practically, this means that iteration may be necessary to ensure that deviation from this assumption does not have a deleterious effect on the model predictions (Norgaard 2000). In this paper, using Multilayer Perceptron (MLP) network to estimate the parameters and predict model output of Eq. 1. The MLP-networks considered here having only one hidden layer and only hyperbolic tangent and linear activation functions (f, F):

$$y_i(w,W) = F_i\left(\sum_{j=0}^{q} W_{ij} f_j\left(\sum_{l=1}^{m} w_{jl} z_l + w_{j0}\right) + W_{i0}\right) \quad (2)$$

Where, $y_i(w,W)$ is the prediction of the model as a function of network weights; w_{j0} and W_{i0} are the bias parameters; m is the number of input units; and q is the number of hidden units. The function f (.) that is implemented in this paper is a tangent function and F(.) is a linear function output. The weights are the adjustable parameters of the network. z_l represents the feature vector of length m, presented to the input of a feed forward neural network.

4. RESULTS AND DISCUSSIONS

The crane oscillation amplitude and frequency with deformation model identification for the three selected points A(X), E(Z) and F(X) can be described as follow:

4.1 Real time acceleration analysis

The real time acceleration analysis of the crane deformations in the time and frequency domains consist of the following steps:-

a) Dynamic displacement calculations:

The acceleration measurements recorded on February 21, 2013 at points A, E and F are converted to the dynamic displacement as shown in Fig. 7. The dynamic displacement is calculated using double integration of the acceleration measurements after de-noised the observations and correction the base integration (Meng et al. 2007). The mean relative dynamic displacements from the acceleration measurements at points A, F and E are presented as shown in Fig. 9. From this Fig., it can be shown that the maximum relative displacements are 8.15mm, 10.71mm and 5.74mm at points A, F and E, respectively. In addition, it can be shown that container-moving load period (crane working period) from 8.00 am to 16.00 pm on this day.

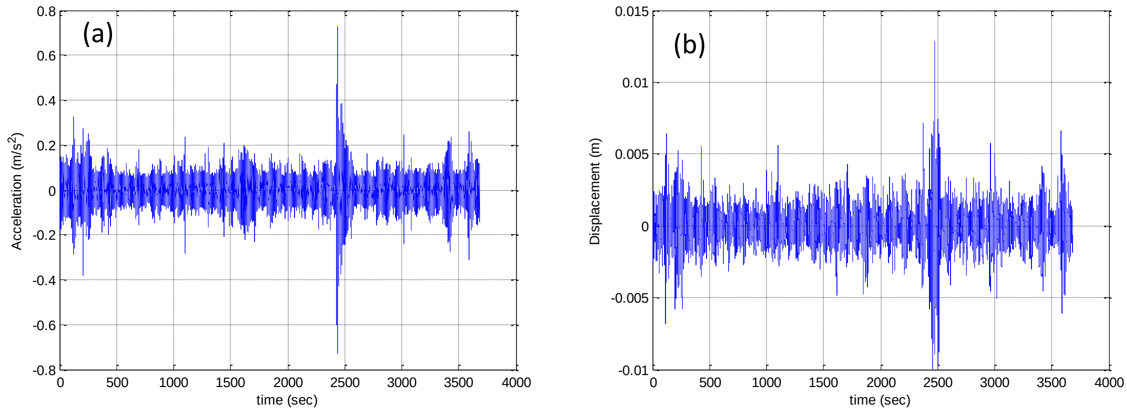


Fig. 7 The acceleration and calculated displacement time histories of point A at 6:00am on February 21, 2013; (a) acceleration; (b) displacement

b) Static displacement calculations:

From the FEM analysis that mentioned in section 3.1, and using the environmental input data shown in Fig. 8 and container-load conditions. The output displacement component in this case is considered a static component of crane deformations as shown in Fig. 9. From this Fig., it can be shown that the maximum relative displacements are 4.40mm, 3.70mm and 8.30mm at points A, F and E, respectively.

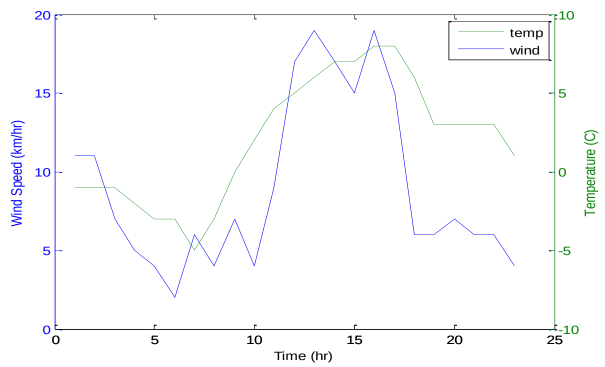


Fig. 8 Average wind speed and temperature on February 21, 2013.

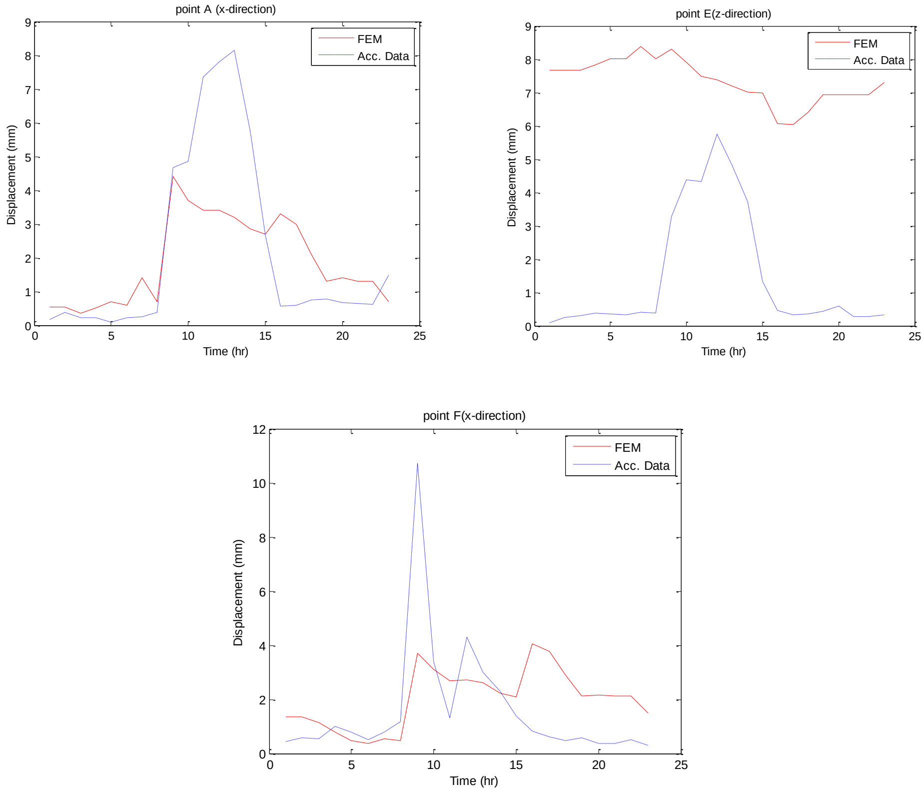


Fig. 9 Relative displacements of acceleration measurements and FEM for points A, E and F on February 21, 2013.

From the relative dynamic and static displacement components comparison, which presented in Fig. 9; it can be seen that the dynamic and static crane displacement components before and after the container-loading period are showing close values for points A and F. Otherwise, at point E the crane displacement components are not matching. This indicates that the rigidity of point E, which represents the connection point of the crane bracing members, affects the static displacement component calculated from the FEM. From these results, it can be concluded that the mean dynamic displacement, which calculated from acceleration measurements, cannot reveal the full crane displacement components under the container-loading case (Psimoulis et al. 2011). However, they can show the static movement of structures under the environmental load case, therefore, it is not easy to calculate the amplitude of the static displacements from acceleration measurements. In addition, the recording point's rigidity is affecting the static displacement components of the structure; therefore, the FEM cannot express the actual behavior of structures at these points.

c) Identification of oscillation frequency:

The spectra of the dynamic components of the acceleration measurements corresponding to the crane loading cases were computed to investigate the existence of an oscillation signal and eventually detect the oscillation frequency. The Fast Fourier Transform (FFT) is used to calculate the first mode of crane displacements as shown in

Fig. 10. From this Fig., it can be seen that the crane loading cases affect the crane frequency mode. The drop in the first mode frequency of the acceleration measurements due to container moving load is 4.9 Hz, 11.49 Hz and 1.36 Hz at points A, E and F, respectively. From Fig. 10 and Table 3, it can be seen that the first mode frequencies of the crane is greater than first mode calculated from the FEM in the different loading conditions. Although, it can be shown that the rigidity of point E is affecting also on mode frequency at this point. From these results, crane displacements are within the safe limits under the different loading conditions, especially under the container-moving load case.

Table 3: The fundamental frequencies from the SAP model and from the acceleration measurements at different points of the carne

Time (hr)	A(x-dir.)	E(z-dir.)	F(x-dir.)	FEM analysis	Load case
5:00 am	5.60 Hz	1.99 Hz	2.06 Hz	0.09 Hz	(ambient conditions)
11:00 am	0.70 Hz	13.48 Hz	0.70 Hz	0.18 Hz	(loading conditions)

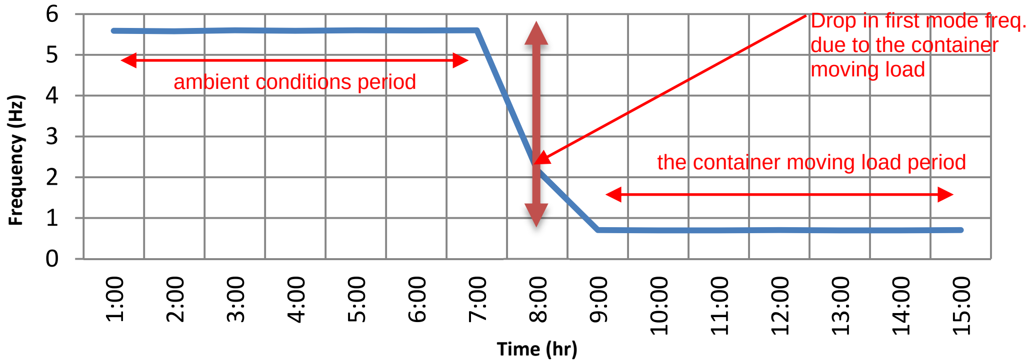
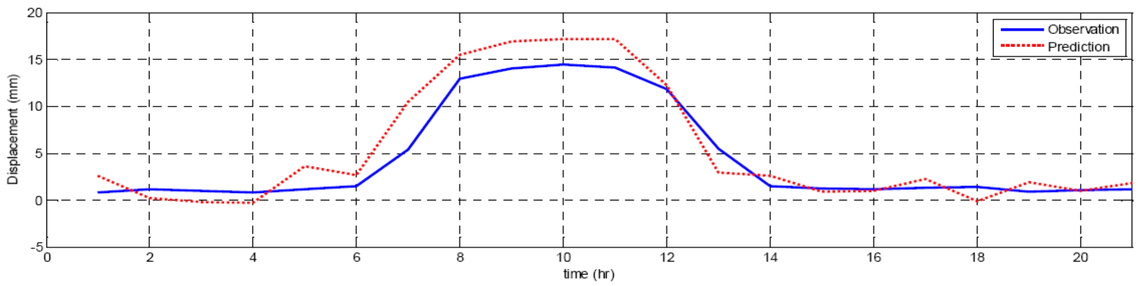


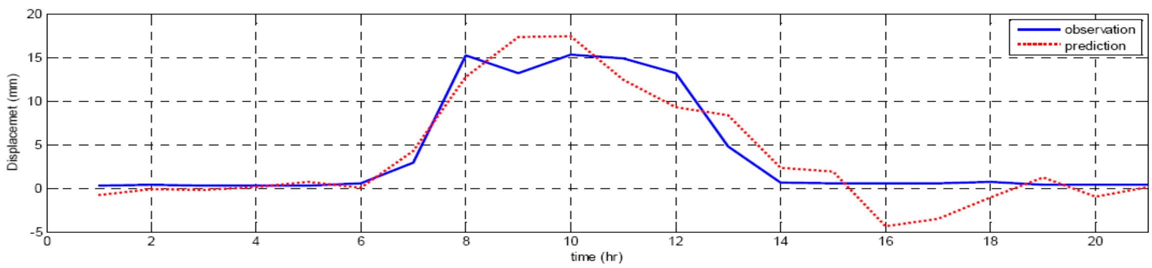
Fig. 10 The fundamental frequencies at point A on February 21, 2013

4.2 Model identification analysis

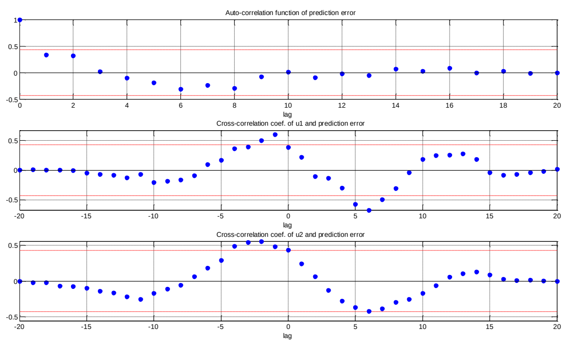
The Neural Network ARX model is used to identify the crane movements at points E and F. The model is design based on the acceleration measurements recorded at point A on February 21, 2013. The designed model based on multi-input single-output (MISO) to identify and to detect the crane movements under affected wind (u1) and temperature (u2) loads as shown in Fig. 8. From Fig. 11, it can be seen that the NNARX [2 2 1] model is suitable to identify the crane movements of point E, whereas the R-Value about 0.92 and the maximum model error is 2.5 mm. Furthermore, it is suitable to identify the movement of point F, whereas the R-Value about 0.84 and the maximum model error is 5 mm. The autocorrelation function (ACF) of prediction errors and 95% confidence intervals and cross correlation coefficients of u1 and u2 with predicted errors and 95% confidence intervals were shown in Fig. 11. From these Figs., it can be show that no loss of information was observed since the residuals of this model stayed within confidence interval of the auto-correlation function and cross-correlation coefficients of u1 and u2. Herein, we can concluded that the NNARX [2 2 1] model is reflect the behavior of crane movement and can be detected the movement of crane at different points of crane. In addition, it can be concluded that the wind and temperature loads effects can be affected on the movement of crane in different cases crane loads.

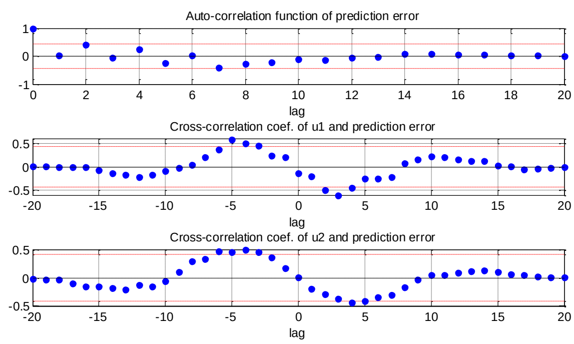


(a)



(b)





(c)

(d)

Fig. 11 a), b) model identification for points E and F; c), d) statistical model for points E and F, respectively.

5. CONCLUSIONS

Based on the limited study of the container crane in Pusan city, the analysis results lead to the following findings:

- The relative mean dynamic displacements of the crane are 8.15mm, 10.71mm and 5.74mm at points A, F and E, respectively. While, the relative static displacements at points A, F and E are 4.40mm, 3.70mm and 8.30mm, respectively.
- The mean dynamic displacements that are calculated from the acceleration measurements cannot reveal the full crane displacement and movement components in case of container-moving loads. However, they can show the static movement of structures under the environmental load case. Therefore, it is not easy to calculate the amplitude of the static displacements from the acceleration measurements.
- The rigidity of connections and members of structures affects the static displacement components of structures.
- The drops in the fundamental frequency values of the acceleration time histories due to the effect of container-moving loads are 4.9 Hz, 11.49 Hz and 1.36 Hz at points A, E and F, respectively. In addition, the fundamental frequency of the crane is greater than the FEM fundamental frequency in the two cases of loading. Furthermore, the rigidity of point E affects the fundamental frequencies of the acceleration measurements at this point. Finally, the crane becomes safe under the container-moving load case.
- The NNARX [2 2 1] model reflects the behavior of the crane movements and can be used to detect the crane deformations at different locations on the crane.

6. ACKNOWLEDGMENTS

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REFERENCES

Bhimani, A. and Soaderberg, E. (2010) “Quay crane accidents: lessons and prevention”, presentation TOC Asia 2010, Shanghai, China.

Chan, W.S., Xu, Y.L., Ding, X.L. and Dai, W.J. (2006) “An integrated GPS-accelerometer data processing technique for structural deformation monitoring”, *Geodesy J.*, **80**:705-719.

Deng, H. and Xu, J. (2009) “Construction safety monitoring and finite element analysis on the supporting system of tower crane in Guangzhou west-tower”, *Proceeding of the Second International Conference on Information and Computing Science,* Manchester, England.

Ding, K.Q., Wang, Z., Lina N. and Song, Q. (2012) “Structural health monitoring system for the crane based on bragg grating sensors”, *Proceeding of 18th World Conference on Nondestructive Testing, Durban, South Africa.*

Kaloop, M. (2012) “Bridge safety monitoring based-GPS technique: case study Zhujiang Huangpu Bridge”, *Smart Structures and Systems*, **9**(6):473-487.

Li, X., Ge, L., Ambikairajah, E., Rizos, C., Tamura, Y. and Yoshida, A. (2006) “Full-scale structural monitoring using an integrated GPS and accelerometer system”, *GPS Solut. J.*, **10**:233-247.

Meng, X., Dodson, A.H. and Reborts, G.W. (2007) “Detecting bridge dynamics with GPS and triaxial accelerometers”, *Engineering Structures J.*, **29**:3178-3184.

Norgaard M. (2000) “Neural network based system identification toolbox”, version2.Tech. Report. 00-E-891, Department of Automation, Technical Un. of Denmark.

Psimoulis P., Moschas F. and Stiros S. (2011) “Measuring the displacements of a rigid footbridge using geodetic instruments and an accelerometer”, Proceeding of JUSDM, Hong Kong, China.

Richard L.N., Seixas, N.S. and Ren, K. (2001) “A Review of Crane Safety in the Construction Industry”, *Applied Occupational and Environmental Hygiene J*., **16**(12): 1106–1117.

Sohn, H., Farrar, C.R., Hemez, F.M., Shunk, D., Stinemates, D.W., Nadler, B.R. and Czarnecki, J.J. (2004) “A review of structural health monitoring literature: 1996–2001”, *Los Alamos National Laboratory Report*, LA-13976-MS.

Zhiping, L., Tengfei, J., Qing, H. and Dang, W. (2011), “Research on mechanical condition monitoring technology for portal crane by wireless sensors”, *Proceeding of 3rd International Conference on Measuring Technology and Mechatronics Automation, Shangshai, China.*