Proactive Maintenance Strategy Based on Resilience Empowerment for Complex Buildings

Francesco Rota[1], Maria Cinzia Luisa Talamo[1],
and Giancarlo Paganin[2(✉)]

[1] ABC Department, Politecnico di Milano, Milan, Italy
[2] DASTU Department, Politecnico di Milano, Milan, Italy
giancarlo.paganin@polimi.it

Abstract. Resilience of the built environment, particularly in complex buildings, is strictly related to the effectiveness of systems and sub-systems that provide the expected features to manage risk scenarios in routine and non-routine conditions. In this perspective, maintenance is therefore a key factor to assure building resilience by keeping systems and equipment in the required operational state. Risk management can be empowered if system resilience and disruptive events are monitored in real-time, and, to this aim, proactive maintenance can nowadays monitor systems resilience with innovative digital tools.

More specifically, proactive maintenance, through Industry 4.0 (I4.0) tools, can enact control strategies for mitigating both endogenous risks – such as equipment failure, aging and obsolesce not always deeply investigated in building sector – and exogenous risks.

Anticipation of disruptive events of systems and control of endogenous risks is possible thanks the introduction of IoT and machine learning tools which may allow to modify the traditional corrective maintenance in the direction of a proactive maintenance approach.

Aim of this paper is to highlight how proactive maintenance approach, if fully implemented, and supported by I4.0 tools, can empower resilience of systems in the building sector.

Keywords: Complex building resilience · Condition-based maintenance · Proactive maintenance · Information management · I4.0 · Risk management

1 Introduction

1.1 Proactive Maintenance Approaches in Support of Infrastructure Resilience

Maintenance, in its general exception, ensures system performances over time. Introducing the exception of proactivity, through real-time data management, maintenance can dynamically support in advance the actions taken in order to:

– prevent the occurrence of a disruptive event;
– monitor the system status, alerting if performances are reaching a critical threshold.

Actual proactive maintenance application needs:

– a real-time data flow management;
– systems able to process real-time data and learn in order to obtain dynamically system predictions and select responding actions.

These conditions can be supported by enabling technologies proposed by Industry 4.0 (I4.0). Through them, by processing a huge amount of data over a limited time frame, proactive maintenance can:

– describe the assets status/performance in a relative short period;
– contribute to highlight the risks of the disruptive events deriving from internal & external hazards.

In this way, proactive maintenance, seen as strategy which describes in advance assets current and possible future status, can empower systems resilience in complex buildings, by dealing with actions - such as anticipate, resist, adapt, react and adjust (ARARA) [1], which withstand the possible changes due to the progressive degradation and the abrupt failures of systems.

Innovation, in the traditional maintenance strategies of complex buildings, consists in the application of IoT, machine learnings and big data - already used in industrial sector – in the management of systems to empower complex buildings resilience.

This paper shows an application of a methodology, tested for the proactive maintenance of equipment, which support the operations of hospital buildings.

2   Complex Systems Resilience Management in the Building Sector

2.1   Current Complex Systems Resilience Approaches in Building Sector

In management of complex buildings, especially where criticalities of systems must be carefully considered, a risk management framework (based on: context analysis, risk assessment, taking control measures, monitoring and review, communication and training) is highly recommended in order to increase their resilience.

Currently, the major attention of risk management seems to focus on natural hazards related to earthquakes, fire, climate change, rather than to the effects of technical events, apparently less dangerous, such as service equipment faults, aging of the systems, cyber-attacks of ICT system or infrastructure incorrect use and so on.

However, these effects are very often those that constitute the principal and most frequent highly-impacting causes in the loss of performance for the systems, so, even on these factors should be necessary to develop a resilience strategy.

By analysing the current literature (Table 1), resilience in complex building management starts to be a hot-topic, investigated from different points of view, in particular those related to some strategic actions (such as anticipate, resist, adapt, react, adjust) and managed with the support of some dynamic tools.

Table 1. Comparison table of resilience references in the building sector.

Authors	Field	Risk	Resilience features	Resilience quantification tool	Levels		
					SOC	ECON	ENV
Hashemi et al. (2019) [8]	Building materials	Collapses	Resist, Recovery, Adapt	Multi-axis hybrid simulation	✓	✓	✓
Khanmohammadi et al. (2018) [11]	Hospital buildings	Earthquakes	React, Adapt	Dynamic simulation for post-recovery	✓		
Yu et al. (2019) [17]	Hospital buildings	Earthquakes	React	Fault tree analysis	✓	✓	
Cimellaro et al. (2018a) [6]	Hospital buildings	General events	React	Questionnaires, Factor analysis	✓		
Kurth et al. (2019) [12]	Building industry	General events	React, adapt	Resilience metrics	✓	✓	
Cimellaro et al. (2018b) [5]	Building and Transportation System	Earthquakes	Resist, react	Performance function, Analytical model	✓		
Hossain et al. (2019) [9]	Power grid	Extreme weather events	Resist, absorb, react	Bayesian Network	✓	✓	
Cho et al. (2019) [4]	Nuclear power plant	Earthquakes	Resist, absorb	Dynamic response analysis	✓		
Rehak et al. (2019) [15]	Energy infrastructure	Cyber-attacks	Resist	Robustness, Adaptability and Recoverability index	✓	✓	
Pantelic et al. (2019) [13]	Buildings	Air pollutant	Anticipate, react	I/O ratio, E-index. IoT technology	✓		

The investigated references highlight some issues:

– The 5 resilience actions (ARARA) are never considered all together at the same time;
– Resilience is mainly assessed through qualitative tools rather than quantitative methods;
– Resilience can benefit through real-time data collection and elaboration system;
– Resilience is mainly considered in relation to risks depending on external high-impact events, rather than to those depending on the outage of equipment;
– Maintenance is normally not considered as a strategy to improve system resilience.

2.2   Proactive Maintenance for Resilience Empowerment

The literature analysis highlights how proactive maintenance strategy may be one of the possible measures for the improvement of the resilience of complex buildings, by the management of:

– the effectiveness of the systems considered as control measures for external hazards
– the hazards related to aging, degrading patterns and disruptive faults of the systems themselves.

In this regard, proactiveness can innovate the traditional resilience approach (Fig. 1 – part A) by anticipating the prediction of the time of failures through the dynamic analysis of real time data enabled by technologies, such as big data, IoT and machine learnings.
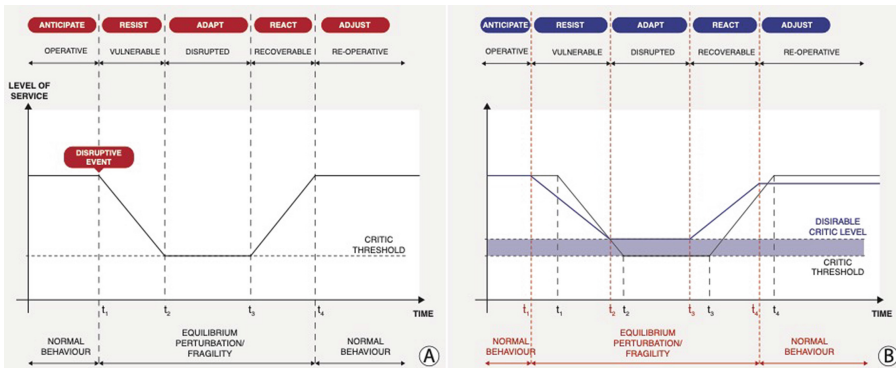

Fig. 1. Resilience approach in traditional (A) and innovative (B) approach

Figure 1 shows the representation of the resilience of a system highlighting the ARARA actions in relation to a disruptive event. The resilience curve can be represented through many control functions related to reliability, availability, resistance and others [1]. The critic threshold represents the minimum level of the service that the complex buildings can stand. This critic threshold doesn't necessarily coincide with the

default state in which the complex building doesn't comply with its intended purpose. After the disruptive event, the fragile phases of complex buildings are represented by the vulnerable, disrupted and recoverable phases.

By applying proactive maintenance, supported by I4.0 tools, the typical resilience actions can be empowered:

– *Anticipate* can be activated through an effective management of information flows, supported by IoT and sensors deployment;
– *Resist* can be supported by monitoring tools, such as automated feedback;
– *Adapt* and *React* can be favored by a support from machine learnings – data-driven model, physical based model and hybrid model – that can help the decision making process. Furthermore, also operational activities may be supported for instance in providing spare parts with 3d printers which can be used for the production of components suddenly necessary;
– *Adjust* can be reached through digital twin [7], platforms and database deployment;

The analysis of the wide current literature (Table 2) highlights the central role of IoT and machine learning in the practice of proactivity. In particular, from the perspective of IoT (Table 2):

– considering the IoT levels (sensors level, communication level and service level), some approaches can be useful for system performance analysis. The big data flow passes through the three different levels, facilitating system prediction analysis and/or performance assessment;
– in the service level data are elaborated and stored. These applications are currently already available also in cloud solutions: PaaS, SaaS and PMaaS, through which proactiveness can be offered as a service;
– services provided through IoT are offered, at present, through data storage form – SaaS, DbaaS – and data analytics form too – BiaaS, BfaaS and FaaS.

Table 2. Comparison table of IoT components is service layer offered as proactive tools.

Authors	Maintenance purpose	IoT components
Evaluation of Predictive-Maintenance-as-a-Service Business Models in the Internet of Things. **Zoll et al. (2018)**	**PmaaS**	Cloud analytics
Software as a Service. **Buxmann et al. (2008)**	**PmaaS**	Cloud analytics
Tradeoffs between performance and security of cryptographic primitives used in storage as a service for cloud computing. **Patel et al. (2012)**	**SaaS**	Cloud storage
Bridging data-capacity gap in big data storage. **Bhat et al. (2017)**	**DbaaS**	Cloud storage and database
Cloud and IoT-based emerging services systems. **Sharma et al. (2018)**	**BiaaS, Bfaas, DaaS**	Cloud analytics

Table 2. (*continued*)

Authors	Maintenance purpose	IoT components
Cloud-enabled prognosis for manufacturing. **Gao et al. (2015)**	**MaaS**	Cloud analytics
Failure as a service (faas): A cloud service for large-scale, online failure drills. **Gunawi et al. (2011)**	**FaaS**	Cloud analytics and storage
Machine learning for predictive maintenance: A multiple classifier approach. **Susto et al. (2015)**	**FaaS**	Cloud analytics
Smart technologies with wireless sensor networks. **Dener and Bostancıoˇglu (2015)**	**PmaaS**	Cloud analytics
Timed verification of machine-to-machine communications. **Gharbi et al. (2014)**	**PmaaS**	Cloud analytics
Emerging trends, issues and challenges in Internet of Things, Big Data and cloud computing. **Kobusińska et al. (2018)**	**PmaaS**	Multi-Cloud
Deadline-constrained coevolutionary genetic algorithm for scientific workflow scheduling in cloud computing. **Liu et al. (2017)**	**PmaaS**	Multi-Cloud
Networking protocols and standards for internet of things. **Salman and Baset (2012)**	**PmaaS**	Multi-Cloud
Development of an earth observation cloud platform in support to water resources monitoring. **Bucur et al. (2018)**	**PmaaS**	Cloud analytics and storage

Business Integration/Intelligent-as-a-Service: **BiiaS**, Business framework-as-a-Service: **BfaaS**, Database-as-a-service: **DbaaS**, Failure-as-a-Service: **FaaS**, Predictive-Maintenance-as-a-Service: **PmaaS**, Software-as-a-Service: **SaaS**.

From the point of view of machine learnings (Table 3):

– transferred data in an IoT architecture are elaborated in a machine learning tool, which can be deployed in a service layer, which provides a system performance prediction.
– different kinds of machine learning (ML) tools can be used, but those which are referred as data-driven model [10] are the most promising, as they use big data originated from the specific components of complex building operations, resulting in more accurate predictions.

The success of an efficient resilience assessment for complex buildings is dependent on an architecture for information management flow, which focuses its strategy on innovative *anticipating* actions (Fig. 1 – part B). In the traditional approach, collected

Table 3. Comparison table of machine learning tools for a data-driven model.

Authors	Information sources	Goal	ML
Multiple fault separation and detection by joint subspace learning for the health assessment of wind turbine gearboxes. **Du et al. (2017)**	Expert knowledge, Sensor data	Identify fault patterns	**JSL**
A novel approach for data-driven process and condition monitoring systems on the example of mill-turn centers. **Kißkalt et al. (2017)**	Sensor data	Degradation pattern recognition	**HMM**
Prognostics and health management: A review of vibration based bearing and gear health indicators. **Wang et al. (2018)**	Sensor data	Life prediction of system	**HMM**
A data-driven method for estimating the remaining useful life of a composite drill pipe. **Lahmadi et al. (2018)**	Sensor data	RULs prediction of system	**RNN**
Intelligent health monitoring of machine bearings based on feature extraction. **Chalouli et al. (2017)**	Sensor data	Fault diagnosis	**KM**, **KM**
Equipment Sub-system Extraction and its Application in Predictive Maintenance. **Zhao et al. (2018)**	Sensor data	Fault detection	**HC**
An Industrial Case Study Using Vibration Data and Machine Learning to Predict Asset Health. **Amihai et al. (2018)**	Sensor data	Prediction of asset health	**RF**
(WIP) Correlation-Driven Service Event Routing for Predictive Industrial Maintenance. **Zhu et al. (2018)**	Sensor data	Prediction of system fault	**ECA**
Tool wear condition monitoring based on continuous wavelet transform and blind source separation. **Benkedjouh et al. (2018)**	Sensor data	Prediction of wear in milling operations	**CWT**
Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction. **Mosallam et al. (2014)**	Nasa prognostic center dataset	RULs prediction of critical components	**KM**
Prognostics of multiple failure modes in rotating machinery using a pattern-based classifier and cumulative incidence functions. **Ragab et al. (2019)**	Sensor data	RULs prediction of critical components	**ANN**, **SVM**
Remaining useful life prediction using prognostic methodology based on logical analysis of data and Kaplan–Meier estimation. **Ragab et al. (2016)**	Sensor data	Survival analysis	**KME**

Table 3. (*continued*)

Authors	Information sources	Goal	ML
Vehicle remote health monitoring and prognostic maintenance system. **Shafi et al. (2018)**	Sensor data	Fault prediction for subsystems	**DT, SVM, KNN, RF**
A Simple State-Based Prognostic Model for Filter Clogging. **Skaf et al. (2015)**	Sensor data	Detect filter clogging	**HMM**
Machine learning for predictive maintenance of industrial machines using IoT sensor data. **Kanawaday et Sane (2017)**	Sensor data	Prediction of failures and quality defects	**ARIMA**
Machine Learning approach for Predictive Maintenance in Industry 4.0. **Paolanti et al. (2018)**	Sensor data, Maintenance logs	Fault prediction	**RF**
Predicting tool wear with multi-sensor data using deep belief networks. **Chen et al. (2018)**	Sensor data	Prediction of wear system	**DBN, ANN, SVM**
Early fault detection of machine tools based on deep learning and dynamic identification. **Luo et al. (2019)**	Sensor data	Fault detection	**DL**
A research study on unsupervised machine learning algorithms for early fault detection in predictive maintenance. **Amruthnath et Gupta (2018)**	Historical data, Sensor data	Fault detection	**PCA, HC, KF, FA**
On the use of machine learning methods to predict component reliability from data-driven industrial case studies. **Alsina et al. (2018)**	Sensor data, Equations	Reliability estimation	**RF, LR, SVM, ANN**
Thermal power generation fault diagnosis and prediction model based on deep learning and multimedia systems. **Chen et al. (2018)**	Historical dataset	Fault diagnosis	**DL, FA**
Towards online data-driven prognostics system. **Elattar et al. (2018)**	Sensor data	Online prognostics system	**DL, KF**
Machine prognostics based on sparse representation model. **Ren et al. (2018)**	Sensor data	Estimation of machines life	**SR, HC**

Artificial neural network: **ANN**, Auto Regressive Integrated Moving Average: **ARIMA**, Blind source separation: **BSS**, Continuous wavelet transform: **CWT**, Deep Belief Network: **DBN**, Decision trees: **DT**, Deep Learning: **DL**, Event correlation algorithm: **ECA,**, Fuzzy Algorithm: **FA**, Health Indicator: **HI**, Hidden Markov Model: **HMM**, Hierarchy clustering: **HC**, Kalman filter: **KF**, K-Means: **KM**, Kaplan-Meier estimation: **KME**, Nearest neighbour: **KNN**, Joint subspace learning: **JSL**, Linear regression: **LR**, Principal Component Analysis: **PCA**, Recurrent Neural Network: **RNN**, Random forest: **RF**, Sparse representation: **SR**, Support vector Machine: **SVM**.

data are used to propose a description of the system. However, the system may be changed during the observation period, causing an outdated description, so a new data acquisition may be necessary. This requires new data collection. In the real time approach, the continuous collection of data, offered by big data, can optimize the time between asset monitoring and performance description ($x \rightarrow \tilde{y}_1$) and behavior predictions over a long period ($x \rightarrow \tilde{y}_2$) within a certain accuracy and uncertainty (Fig. 2).

By adopting such tools, complex buildings management can display proactiveness, by improving the accuracy of these predictions.
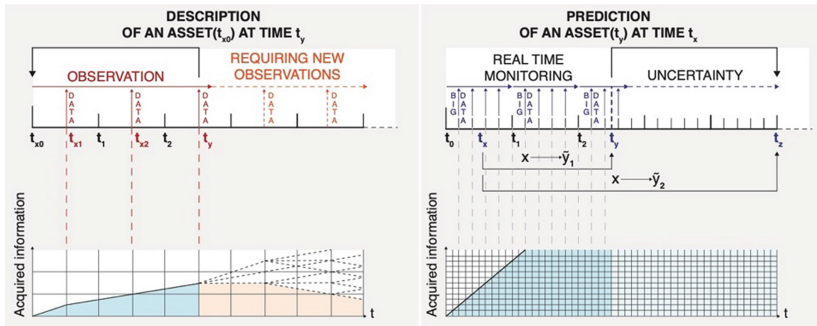
Fig. 2. Acquired information from an asset with traditional and innovative approach.

3 Proposal of a Proactive Maintenance Framework for Dynamic Information Management of Complex Building Resilience

On the basis of the above described innovative scenario, this paper presents a research aiming to develop a proactive maintenance procedure for complex building. Innovation is offered by the opportunity of taking advantage of data-driven model in the building sector, to develop a proactive approach, mainly used in the industrial sector.

Proactive maintenance in complex buildings - such as hospitals, airports, stations and office buildings – supported by IoT and machine learnings, can have an appropriate application especially in critical systems (such as Heating, ventilation, air conditioning & refrigeration – HVACR, electrical, ICT, conveying, plumbing and fire protection). In addition, the inclusion of I4.0 tools can integrate the existing supervisory systems, such as Supervisory Control and Data Acquisition, Building Management System (BMS), Enterprise Resource Planning, Computerized Maintenance Management System and Information System (SI). When big data are stored, in a physical database or in a cloud storage, they can be analyzed through a machine learning tool aiming to build a data-driven model.

Among the current data-drive models, the Recurrent Neural Network (RNN) seems to be the most promising one for its capacity to: store useful data; remember the history related to normal behavior of assets; ignore the irrelevant information.

The conditions for the use of RNN is to have a labelled benchmark dataset, in which:

- failures of assets are registered (typically performed in a SI);
- failures are abundant over a period, so that a failure pattern can be recognized;
- different variables, for normal and abnormal behavior, in the form of big data, are continuously and massively acquired in time laps of 1-15 min;
- at least a reasonable amount of data is available (typically 1 year or more of stored data to be split in 70–80% of trainset and 30–20% of testset).

RNN architecture is composed of a multi-structure of neurons which elaborate, according several loops, the acquired information (such as monitored temperature and electrical values, typically tracked by control systems). Vibration, electric and temperature sensors can be used to collect data and transfer it in a preprocessing phase.

Acquired data are then transformed - according to Root Mean Square and Kurtosis value or Fourier Transform - and stored in relational tables in the form of numeric values. The process of prediction with a RNN is composed of some steps: (i) preprocessing phase to transform input big data into output vectors to further feed RNN; (ii) a data normalization phase through a MinMax Scaling technique to have more uniformed dataset. The normalization is needed, in the learning process, especially if several series of different amplitude are recorded through sensors; (iii) train phase; (iv) test phase.

If RNN needs to be used to model for long-term dependencies, it can be structured as a Long Short-Term Memory RNN network (LSTM) in Fig. 3.

LSTM have the form of a chain of consequential modules (Unit State) of neural network, with the main difference of LSTM consisting in Units of 4 neural network layers, interacting according special gates.

In each LSTM Unit there is a horizontal information flow, like a conveyor belt where data are processed in the entire chain. Each LSTM Unit State has three gates where an input gate controls if the unit memory is updated, a forget gate monitors if the unit memory is reset to zero and an output gate verifies if the information of the current unit state is made visible. All the three gates use a sigmoid activation function to describe how much of each component should be transmitted. A value of 0 refers to not letting through any value, while a value of 1 means letting through the value, in order to make the model differentiable.

The desired output of LSTM is to know the time-to-failure of a HVAC system, according to the change of input variable over the time, according its operative performance.

The knowledge of this variable allows to further implement strategies for improving system resilience and reducing risks.
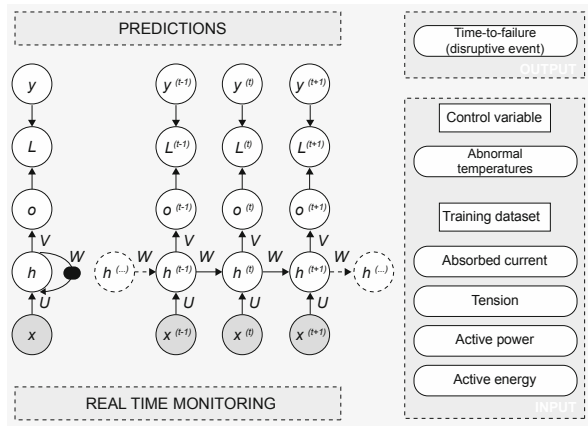
Fig. 3. Structure of a LSTM-RNN with input data coming from a typical HVAC system.

4   Conclusion

Resilience in complex buildings represents a hot topic in the correct management of the critical systems. Innovation in building resilience can nowadays be leveraged through IoT and machine learning by enabling proactive maintenance.

Proactive maintenance, seen as an innovative approach in the construction sector, can introduce in the management of complex buildings the opportunity to anticipate failures and possible consequent changes in the hazard framework or in the effectiveness of the control measures, which could jeopardize systems resilience.

Applications of proactive maintenance approach to increase building resilience can be performed in the management strategies of different complex buildings (such as hospitals, airports, stations, warehouse, etc.…) especially where equipment are intensively used in daily operations and play a key role in resilience performances.

Current IoT and machine learnings tools, which exploit data extracted directly from the systems, can help to build a proactive strategy, which pursues anticipation (knowledge, decision, actions), that can effectively improve the robustness of resilience plans empowered through enabling technologies that support resist, absorb, react and adapt actions.

References

1. Bie, Z., Lin, Y., Li, G., Li, F.: Battling the extreme: a study on the power system resilience. Proc. IEEE **105**(7), 1253–1266 (2017)
2. Ceferino, L., Mitrani-Reiser, J., Kiremidjian, A., Deierlein, G.G.: Computing Hospital System Resilience: A Supply-Demand Perspective (2018)
3. Chen, Y., McCabe, B., Hyatt, D.: A resilience safety climate model predicting construction safety performance. Saf. Sci. **109**, 434–445 (2018)

4. Cho, S.G., Furuya, O., Kurabayashi, H.: Enhancement of seismic resilience of piping systems in nuclear power plants using steel coil damper. Nucl. Eng. Des. **350**, 147–157 (2019)
5. Cimellaro, G.P., Arcidiacono, V., Reinhorn, A.M.: Disaster resilience assessment of building and transportation system. J. Earthq. Eng., 1–27 (2018b)
6. Cimellaro, G.P., Malavisi, M., Mahin, S.: Factor analysis to evaluate hospital resilience. ASCE-ASME J. Risk Uncertainty Eng. Syst. Part A Civ. Eng. **4**(1), 04018002 (2018a)
7. Farsi, M.A., Zio, E.: Industry 4.0: some challenges and opportunities for reliability engineering. Int. J. Reliab. Risk Saf. Theor. Appl. (2019)
8. Hashemi, M.J., Al-Attraqchi, A.Y., Kalfat, R., Al-Mahaidi, R.: Linking seismic resilience into sustainability assessment of limited-ductility RC buildings. Eng. Struct. **188**, 121–136 (2019)
9. Hossain, N.U.I., Jaradat, R., Hosseini, S., Marufuzzaman, M., Buchanan, R.K.: A framework for modeling and assessing system resilience using a Bayesian network: a case study of an interdependent electrical infrastructure system. Int. J. Crit. Infrastruct. Prot. **25**, 62–83 (2019)
10. ISO 13381:2015 - Condition monitoring and diagnostics of machines
11. Khanmohammadi, S., Farahmand, H., Kashani, H.: A system dynamics approach to the seismic resilience enhancement of hospitals. Int. J. Disaster Risk Reduct. **31**, 220–233 (2018)
12. Kurth, M.H., Keenan, J.M., Sasani, M., Linkov, I.: Defining resilience for the US building industry. Build. Res. Inf. **47**(4), 480–492 (2019)
13. Pantelic, J., Dawe, M., Licina, D.: Use of IoT sensing and occupant surveys for determining the resilience of buildings to forest fire generated PM2. 5. PLoS One **14**(10) (2019)
14. Patriarca, R., Di Gravio, G., Costantino, F., Falegnami, A., Bilotta, F.: An analytic framework to assess organizational resilience. Saf. Health Work **9**(3), 265–276 (2018)
15. Rehak, D., Senovsky, P., Hromada, M., Lovecek, T.: Complex approach to assessing resilience of critical infrastructure elements. Int. J. Crit. Infrastruct. Prot. **25**, 125–138 (2019)
16. Yan, S., Lin, K.J., Zheng, X., Zhang, W.: Using latent knowledge to improve real-time activity recognition for smart IoT. IEEE Trans. Knowl. Data Eng. (2019)
17. Yu, P., Wen, W., Ji, D., Zhai, C., Xie, L.: A framework to assess the seismic resilience of urban hospitals. Adv. Civ. Eng. (2019)