Resilience Supported System for Innovative Water Monitoring Technology

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Abstract. The level of intelligence in monitoring & controlling systems are increasing dramatically. The critical issue for an autonomous resilient system is detecting the anomalous behavior through standard patterns to react properly and on time. In cyber-physical systems with the interaction of humans and machines, this will be more complicated. Deceptive alarm is a common dilemma in real systems which could reduce awareness and readiness and accordingly resilience of the system. In this paper, Markov modeling technique is used to predict human behaviors patterns to distinguish between human anomalous behavior and system failure. The data is from the real experience of implementing innovative monitoring system in a five-star hotel which was part of the project of gamification for changing guests' behavior. The idea was to develop Resilience Supported System to decrease the fault error and alarms and to increase the reliability and resilience of the system.

Keywords: Performance Assessment, Markov Modeling, Behavior-change Systems, Resilience Supported System, Deceptive alarm.

1 Introduction

In commercial buildings, Building Automation Systems (BASs) are responsible for considerable savings in water and energy consumptions [1, 2], while the performance of the system is affected by consumption behavior of users.

An example can be made in the hospitality industry. In hotels, the execution of automatic energy management system is tied to heating, cooling, and light comfortability of guests including their consumption behavior. On the other hands, hotel managers are always concern about the experience of guests in rooms and never accept novel BAS solutions which threaten the comfortability of customers during their stay. So, more complexity will be added to BAS when it is affected by different elements at the same time.

The Optishower as a technology is an electricity, gas and water consumption monitoring system in hotels. The monthly, weekly, daily and real-time consumption graphs in the application show the consumption performance of the building and can be implemented in cost reduction strategies.

Optishower applies both hardware and software technologies in a smart integrated platform. The ultra-low power consuming data transfer technology makes it possible to take advantage of installing smart Internet of Things (IoT) sensors measuring water and electricity consumption without any destructive intervention in water and electricity infrastructure of buildings. All measured consumption data is sent to a data transmission gateway to be delivered to the data analysis and decision-making platform in the cloud. Finally, this data will be shown to related technicians, managers, and individuals to consider them via interactive and smart online platform.

This service aims to increase the profit margin of the hotel by reducing water and electricity consumption. It works by creating awareness about environmental impacts of consuming water and electricity and motivating hotel guests to use water and energy in a wiser and eco-friendly manner.

Long-term influence prediction of educational interventions on adolescents' development based on the evolutionary causal matrices (ECM) and the Markov Chain has been developed through MATLAB by [3]. They created a computational model predicting longitudinal influences of different types of stories of moral exemplars on adolescents' voluntary service participation and verified the algorithm through surveyed data. The adaptive and automated decision-engine for improving the inherent resilience of autonomous systems has been presented in [4]. Reference [5], proposed new concepts on grid operation considering unexpected extreme disturbances and energy resources with leveraging distribution. In [6], low-cost detection methods have been identified, and novel guidelines for recovery and diagnosis has been provided with focusing on hard faults. Exploring the literature review it shows that there is no previous research work to employ Markov model in case of probabilistic BSC modeling. In this paper the main objective is to use Markov model to solve this challenge in the resilience support topic.

The organization of this paper is as follows. In section II, the contribution of this study in resilience systems will be presented. Section III introduces the innovative technology for water metering. Section IV proposes the probabilistic solution based on Markov chain for Behavior Change Systems (BCSs). Hypothetical and experimental results will be addressed in section V. The use of the proposed solution for resilience improvement of a system will discuss in section VI. Finally, the paper terminates with conclusions and future works.

2 Relationship to Resilient Systems

Resilience is widely recognized as a new paradigm and system designers, inspired by nature, are trying to improve the performance of the human-made systems to provide the capability of dealing with any disorder. The resilient system could be seen as the next generation of the robust or agile system. The resilient system works based on simple fact that it could recognize the attack or abnormal behavior and try to recover using its capability. This will help to reduce the level of the vulnerability of the system and to make sure that they could work effectively in an uncertain environment. Although the main challenge in resilient systems is how to recover and to react according to the input of the system but fault detection and recognizing unacceptable behavior is the trigger of the process which is a common challenge in all types of self-organizing system. In Cyber-physical systems, in which the output is the combination of both machine and human behavior, it would be difficult to distinguish the abnormal behavior by its cause. The challenge of the autonomous and intelligent system is how to detect a deviation and avoid fault error or alarm. In case of frequent deceptive alarms, the sensitivity of the operators will be decreased, and this will reduce the readiness and awareness of the system operators and increase the risk. Resilience support system, which is introduced in this paper, is a kind of decision support system based on Markov modeling technique to separate human behavior of system failure from machine failure. In this work, we use the experience and the database from the implementation of innovative technology which was selected by a five-star hotel as a solution for monitoring water and energy. Fig 1. Illustrates innovative water consumption measurement called Optishower. The main mission was to use gamification and by producing feedback for hotel guests, help to change the behavior which means here decrease the amount of water and energy used by them.

Fig. 1. Optishower system demonstration

The sensors which are monitoring each room of the hotel are sending the data online, and separately. Aay strange behavior could be because of one of these reasons:

a) Problem in water system such as water leakage

b) Problem in monitoring system such as calibration of the sensors

c) Strange human behavior

The first two problems could be categorized as a system failure which needs immediate recovery while the third one is just a result of unexpected guest behavior. Output analysis of the data will just show that something is wrong, but it was important to distinguish between human behavior and system failure. Sensors represent aggregation of both human and machine behavior, and it is important to understand that in case of alarm, what is the probability of machine failure. The challenge of using this new technology is to distinguish between the anomalous behavior of the system and humans. The importance of the proposed resilient support system increases simultaneously with the increase in the number of sensors/rooms, and it is very helpful when we are talking about thousands of rooms/sensors.

3 Probabilistic Modeling

This section studies the probabilistic modeling and calculation of water consumption behavior in case of applying the “Optishower” BCS on five-star hotel guests.
Consider the random discrete signal *x(t)* as the water consumption measurement with sampling time h, and it is associated threshold x_{tp}. For the primary classification mechanism, a person will be considered as a non-eco-friendly guest if *x(t)* exceeds x_{tp}. Otherwise, he/she will be regarded as an eco-friendly guest.
After categorizing eco-friendly and non-eco-friendly consumptions data, the probability density function of them can be obtained as illustrated in Fig. 2.

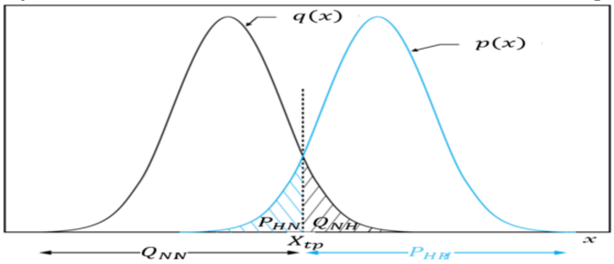


Fig. 2. Both pdfs of eco-friendly and non-eco-friendly water consumption

Having separated pdfs of eco-friendly and non-eco-friendly parts of the signal related to water consumption, the probability of becoming a non-eco-friendly for an eco-friendly type person can be calculated as follows:

$$P\_EF\_to\_NEF = \int_{x_{tp}}^{+\infty} q(x)dx \quad \textbf{(1)}$$

where q(x) is the probability density function of eco-friendly part of water consumption signal x(t) and *xtp* is a simple threshold that classifies the eco-friendly and non-eco-friendly consumptions. Similarly, the probability of becoming a EF for an NEF type person can be computed with the following expression.

$$P\_NEF\_to\_EF = \int_{-\infty}^{x_{tp}} q(x)dx \quad \textbf{(2)}$$

where p(x) is the probability density function of non-eco-friendly part of water consumption signal x(t).
Consider a stochastic process X that takes on a set of M which is finite and countable. The set of *M* has two elements engaged (E) and not engaged (NE). Having applied gamification or awareness strategy, the hotel guest will have eco-friendly consumption in case of being engaged and non-eco-friendly consumption in case of not being engaged with the strategy. Given an observed sequence of engagement states, the transition frequency $F_{N,NE}$ in the sequence can be found. Each element of one-step transition frequency matrix can be obtained by counting the number of changes from state E to NE in one step. The constructed frequency transition matrix for the sequence of the hotel guest engagement is as follows:

$$F = \begin{bmatrix} F_{N,N} & F_{N,NE} \\ F_{NE,N} & F_{NE,NE} \end{bmatrix} \tag{3}$$

Using (4), the probability of each transition in equivalent Markov model can be estimated [7]. In this section, the two-states Markov model is considered (m = 2).

$$P_{N,NE} = \begin{cases} \dfrac{F_{N,NE}}{\sum_{N=1}^{m} F_{N,NE}} & if \sum_{N=1}^{m} F_{N,NE} > 0 \\ 0 & if \sum_{N=1}^{m} F_{N,NE} = 0 \end{cases} \tag{4}$$

Having estimated probabilities of Markov model transitions, the transition matrix can be achieved as (5).

$$P = \begin{bmatrix} P_{N,N} & P_{N,NE} \\ P_{NE,N} & P_{NE,NE} \end{bmatrix} \tag{5}$$

In order to calculate the transient probability from the Markov model, equation (6) can be recursively solved if $P(0)$ is known.

$$P(n\Delta t) = P^{n}.P(0) \tag{6}$$

If the Markov model satisfies the limiting probabilities in (7), then it will be irreducible ergodic Markov chain. Being independent of the initial state, from (8) the steady-state probabilities can be achieved.

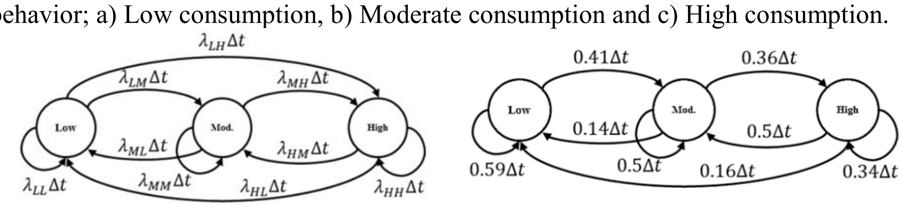
$$\pi_{NE} = \lim_{l \to \infty} P_{N,NE}^{(l)} > 0 \tag{7}$$

$$\Pi = \Pi P, \sum_{NE} \pi_{NE} = 1 \tag{8}$$

where $\Pi = [\pi_1, \pi_2, \ldots]$.

4 Real Case Study

In this section, a real case study in a five-star hotel we are considered. To protect the data privacy of the hotel the name and the city will not be mentioned. In this case study, five different rooms are considered, and data of electricity and water consumption are stored in a cloud-based database. Fig. 3-a shows the typical three-state Markov model of behavior change system in water consumption. This model has three states of behavior; a) Low consumption, b) Moderate consumption and c) High consumption.



(a) (b)

Fig. 3. Three-states Markov model of BCS in water consumption; (a) Typical, (b) Real model.

Based on recorded data and provided theory in the previous section, the three-state Markov model of BCS in cold water consumption is illustrated in Fig. 3-b. The model provided from 35 guests in five different rooms, and the average duration of using a room in the hotel was two days. Having modeled BCS in cold water consumption through Markov model as Fig. 3-b, the Fig. 4 can be provided. In this figure, the green curve shows the probability of "Low" state in the cold-water Markov model and the pink and red curves are showing the probability of states "Mod." Moreover, "High" respectively. As can be seen in this figure, from the beginning the probability of low consumption of cold water after applying the BCS will increase continuously, and the probability of high consumption of cold water will decrease continuously. The probability of state "Mod." Increases in two first days and after that will decreases. All probabilities will be steady-state after ten days.

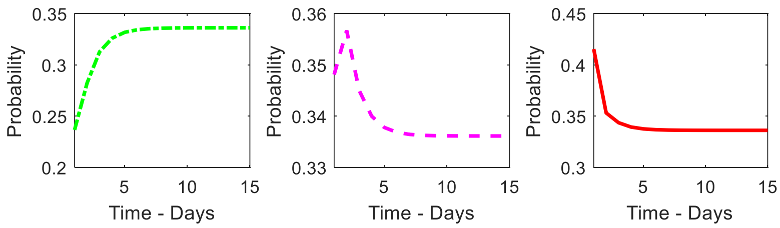


Fig. 4. Prediction based on Markov chain illustrated in **Fig. 3-b**

5 Resilience-Supported System

In this section, the question of how the Markov model can be used as the resilience-supported system will be explained.

Fig. 5 illustrates the block diagram of the proposed resilience supported system based on Markov model. As it mentioned in the previous section, through the Markov modeling, the behavior-change of a hotel guest in water consumption can be estimated. In the proposed system, real-time monitoring of a hotel guest water consumption is available. Any change in water consumption of the hotel guest can be detected by the "behavior change detector" block. It also can categorize the range of water consumption of a guest into three levels; a) Low consumption, b) Moderate consumption and c) High consumption. In parallel, the time-variate Markov-based estimation of behavior-change in water consumption is available. Having counting clock, real-time state of consumption and estimated state of consumption, the final block can be used to formulate those inputs and generate a wise decision.

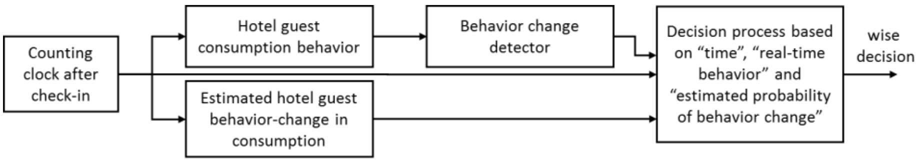


Fig. 5. Markov-based resilience supported system

For example, if the consumption is increasing in the second day of the stay of a person and it is not what we are expecting due to the promotion and gamification process, the first assumptions could be unexpected human behavior, water system failure or monitoring system failure. To understand better the system and the probability of the machine failure (case 2 & 3), the result should be compared with "estimated hotel guest behavior change in consumption" to see if the pattern is following the estimation or not. This is the key factor to recognize the type of failure.

If our estimation which is based on the model shows that the probability of unexpected human behavior is high, it means that the probability of machine failure is low and vice versa as they act unlike each other. This is the first step for any resilient system as the detection is a key factor for any recovery reaction. In case of having thousands of rooms, we have first to check the data comparing with our estimation, the probability of unexpected behavior coming from Markov model, and in case of lack of evidence to show that it could be the result of human behavior, we should immediately check if the monitoring system has a problem or it could be leakage problem in pipes.

6 Conclusion

In this paper, supported resilience system was developed based on Markov model to reduce the problem of Deceptive Alarm in human-made systems while the interaction of machine and human could mislead monitoring system operators. The basic assumption in this work is the fact that unexpected behaviors could be a result of human behavior so before reaction, we should make sure about the probability of the failure of the machine. In innovative IoT based system, this will help not to lose the concentration due to the frequency of alarms which is a common dilemma in monitoring systems while we are talking about thousands of sensors in different geographical hotels. The first step in all resilience system is to detect the disorder to react, and Resilience Supported System helps to increase the efficiency of the resilient process by detecting Deceptive alarms. The system was developed for an Innovative Water Monitoring Technology, and proposed model was tested in a real 5-star hotel to evaluate its applicability.

This work is ongoing research and the next step is to use "Fuzzy Inference System" to aggregate different criteria including the result from Markov model to determine the level of the risk of machine failure vs human unexpected behavior. This will help the operators to act according to the result of the intelligent support system using the analysis of Markov model. Also considering large amount of data (big data) from different rooms and over time, effective variables could be recognized to increase the accuracy of the system.

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