Holistic Design Platform for Sustainable and Resilient Building Design

Umberto Alibrandi
Associate Professor, Dept. Engineering, Aarhus University, Aarhus, Denmark

Khalid M. Mosalam
Taisei Professor of Civil Engineering & PEER Director, Dept. of Civil & Env. Eng., Berkeley, CA, USA

ABSTRACT: In this paper we introduce the Societal Holistic Design Platform (HDP) under uncertainty for sustainable and resilient building design. The integration of classical Risk Analysis, Stochastic Dynamics, Structural Health Monitoring, multicriteria Decision Making, Artificial Intelligence and IoT, gives rise to an innovative Cyber-Physical System under uncertainty centered around humans. The potential of the platform is presented through developed applications. Although the HDP is here applied to a building, it can be easily extended to any system of civil engineering. The proposed platform aims to lead the paradigm shift from the existing notion of Smart City to Resilient Engaged Community, targetting the sustainable development of the urban communities

1. INTRODUCTION

The Disaster Risk Reduction aims to achieve sustainable development of the urban communities by reducing the damages and the losses caused by natural and man-made hazards. This may be achieved only through a human-centric approach, providing the integration of the disaster risk reduction into private investments and public policies. It is known that "natural disasters actually do not exist, only natural hazards do". Disaster risk may be reduced by strengthening the resilience of the built environment, through wise environmental management, and introducing *novel standards for integrated design under uncertainty of smart buildings*.

A building is resilient if, after a hazard occurs, it shows an acceptable level of damage and its recovery time is sufficiently reduced [Bruneau et al. (2003); NIST (2016)]. The lifecycle cost represents the total cost incurred by the building during its life, and it is given by the sum of the construction cost and any operation, repair/retrofit, downtime, and demolition including recycle costs through the life of the building. The latter incorporates the contributions of repair costs of structural and non-structural components. The repairs can be necessary to restore the building conditions before any damages experienced due to natural or man-made hazards, or by environmental phenomena, such as corrosion or material degradation. To prevent any extreme event from becoming a disaster, there is the need to satisfy a consistent and uniform reliability level for all residential and commercial buildings. This can only be achieved through a risk-informed analysis of the safety of the structures. To this aim, knowing the conditions and performances of the different components of a building during, and after a disruptive event is crucial. This reveals the critical need for real-time monitoring, understanding and modeling of the components of the building system (e.g. soil, foundation, structures, non-structural elements like envelope) to predict and improve the building performances.

The sustainability is the "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [WCED (1987)]. The lifecycle $CO2$ emission is equal to the total emission during the construction stage plus that during the entire lifecycle. The emission of $CO2$ depends not only on the energy consumption of the buildings in service conditions for chosen energy scenario, but also on any needed post-hazard repairs. Although sustainability and resilience are typically distinct objectives and quantifiable metrics, we claim that a "green" building needs to be resilient, because of post-hazard repairs, as discussed above. Research has shown that a more resilient building provides less environmental impact along the lifecycle. Interestingly, it is also more advantageous from an economical point of view. Thus, green and energy efficient buildings should be designed to be resilient [Mosalam et al. (2018); Alibrandi and Mosalam (2018b)].

In the current engineering practice, the design process of buildings is generally divided into architectural design, structural design and facility engineering design. We claim that the optimal building design needs to be defined through a holistic view with comprehensive participation of all the members of the different design teams and of the various stakeholders. The efforts of several multidisciplinary designers and stakeholders will be coordinated, giving rise to a harmonious and unified design through the integrated architectural/structural/facility design process. This process is expected to mainly focus on development of tools for holistic implementation of sustainability and resilience, e.g. energy modelling, building performance simulation, lifecycle analysis, decision making under uncertainty, in addition to the safety against extreme events induced by multi-hazards.

To this aim, the integrated design process needs to consider all the different life-cycle phases: Design, Construction, Operation/Maintenance, up to Demolition or Renovation. In literature the existing methods evaluate the lifecycle cost analysis of the buildings, energy efficiency or CO_2 emissions, however no platform develops a comprehensive consideration of the uncertainties within a holistic view during the entire building lifecycle. Moreover, the essential role of people, stakeholders and decision makers (i.e., needs, preferences, capacities, and behaviors) has not been included in the design process.

To fill this gap, in this paper we introduce a Socio-Technical Holistic Design Platform (HDP) under uncertainty, able to provide holistic, multidimensional, and multi-stakeholder integrated design under uncertainty of a smart building. Some examples describe the potential of the proposed platform.

2. Holistic Design Platform (HDP) under uncertainty

Fig.1 shows the schematic of the HDP. It is based on the worldwide adopted Performance-Based Engineering (PBE) approach developed through a framework based on Bayesian Networks (BN) [Jensen and Nielsen (2007)], as described in [Alibrandi and Mosalam (2017a)].

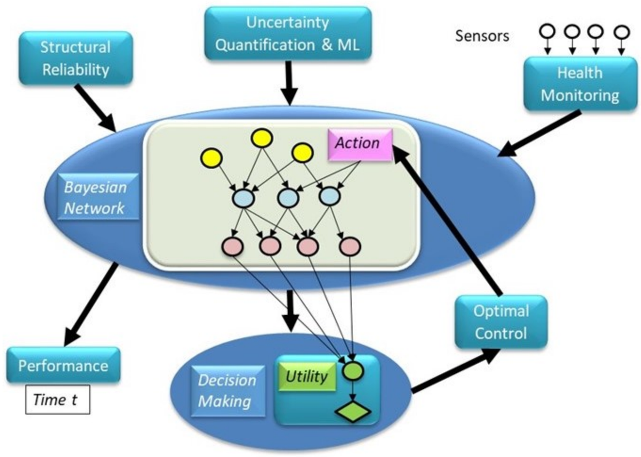

Figure 1: Socio-Technical Holistic Design Platform

The PBE methodology is extensively used for evaluating system performance measures meaningful to various stakeholders, e.g. monetary losses, downtime, and casualties [Cornell and Krawinkler (2000); Gunay and Mosalam (2013); Alibrandi and Mosalam (2018a)]. PBE links, in a natural way, the system design to the desired performances. For this reason, from PBE emerges principles of both resilient and sustainable holistic building design or mitigation actions during the lifecycle.

The PEER PBEE methodology consists of four successive analyses: hazard, structural, damage, and loss. PBE is also a viable solution to estimate the performance based on other criteria such as construction and maintenance costs, CO_2 lifecycle emission, and energy consumption. The HDP has the following main submodules: Uncertainty Quantification (UQ), Reliability Analysis, Structural Health Monitoring (SHM), Decision Making Tool, Optimal Control.

In Fig.2 it is shown the SinBerBEST office, located in CREATE Tower, Singapore. In the building there is a network of sensors which allows to monitor in real-time several parameter of interests, e.g the energy consumption, temperature, humidity, floor acceleration, etc. The data are saved in a Process Information (PI) server, which is a real-time data application developed by OSIsoft with a highly efficient time-series database.

There is a two-way coupling between the HDP and the PI server, so that: (*i*) the data are updated in real time and accessed by the platform, (*ii*) the module of Uncertainty Quantification (UQ) models the time-dependent probability distributions of the uncertain quantities, (*iii*) the module of risk analysis simulates through MCS selected performances, (*iv*) the multi-criteria decision making module explores the consequences of different design alternatives (novel design concepts, technologies and materials), or actions (e.g. operation/maintenance) during the lifecycle.

In Fig.3 a simple example is shown. The HDP reads from the PI server the data of energy consumption (EC) of a user (panel top left of the figure), in a chosen time interval. The module of UQ evaluates the probability distribution of the daily EC of the user (in the panel on the top right the complementary CDF is shown), and the module of risk analysis through MCS simulates the expected EC of the user in an year (panel on the bottom right)

3. Decision support tool under uncertainty

3.1. Generalized Expected Utility (GEU)

In the theory of decision under risk, the main focus of the decision maker is the choice of the optimal solution with respect to a chosen performance G given a set of m alternatives $G^{(i)} = G[\mathbf{x}^{(i)}, \mathbf{v}\{\mathbf{x}^{(i)}\}]$, $i = 1,2,\ldots,m$. The vector $\mathbf{x}^{(i)} = \{x_1^{(i)}, x_2^{(i)}, \ldots, x_n^{(i)}\}$ collects all the design variables

Figure 2: CREATE Building, SinBerBEST Office, Singapore

containing the control variable values representing the set of preselected alternatives. The vector $\mathbf{v}(\mathbf{x}) = \{\mathbf{v}_B(\mathbf{x}), \mathbf{v}_D(\mathbf{x})\}$ collects all the uncertain parameters appearing in the decision-making problem where $\mathbf{v}_B(\mathbf{x})$ collects the basic random variables, which are the parameters that cannot be controlled by the decision-maker, e.g. environmental conditions, while $\mathbf{v}_D(\mathbf{x})$ collects the derived parameters that are affected by the design variables, e.g. responses of the system to the environmental conditions.

The optimal choice is determined through the definition of a functional $V(\cdot)$ applied to the performance G, such that if $V\left(G^{(1)}\right) \geq V\left(G^{(2)}\right)$, then

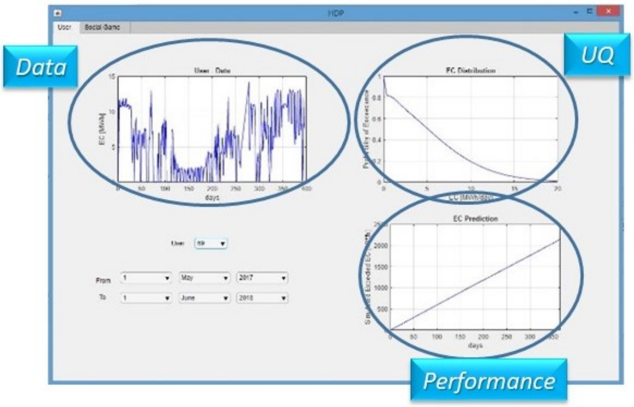

Figure 3: HDP applied to a smart Building

the alternative $G^{(1)}$ is preferred over the alternative $G^{(2)}$. In the utility theory, the alternatives are ranked through the utility function, which converts the values of the performances to scores representing the degree of preference of the decision maker within the decision model. In the HDP we adopt the Generalized Expected Utility (GEU) [Mosalam et al. (2018)] expressed as follows,

$$GEU^{(i)} = \int u^{(i)} \, d\, h\left[\left(F_U^{(i)}\right)\right] \tag{1}$$

where $u^{(i)}$ is the utility of the ith alternative, $F_U^{(i)}$ is its Cumulative Distribution Function (CDF), while $h(\cdot)$ is a suitable function describing the risk perception of the decision maker. The GEU embodies a distinction between the attitudes to the outcomes, measured by $u(g)$, and attitudes to the probabilities, distorted through $h(F_U)$. The optimal decision maximizes the GEU.

If the probabilities are not distorted by the risk perception of the decision maker, i.e. $h(F_U) \equiv F_U$, then the GEU coincides with the largely adopted Expected Utility EU [Von Neumann and Morgenstern (1944)].

$$\begin{aligned} GEU^{(i)} \equiv\; & E\left[U^{(i)}\right] = \int u^{(i)} \, d\, h\left[\left(F_U^{(i)}\right)\right] \\ & = \int u(g) \, dF_G^{(i)}(g) \equiv EU^{(i)} \end{aligned} \tag{2}$$

where $F_G^{(i)}$ is the CDF of the performance G. In the literature, some researchers state that a rational decision maker should be risk-neutral by considering complete consequence models. Under this further assumption, then $u(g) = g$ and

$$GEU^{(i)} = \int g \, dF_G^{(i)}(g) \equiv E\left[G^{(i)}\right] \tag{3}$$

The optimal alternative provides the maximum GEU, i.e.

$$\max_{G^{(i)}} GEU \equiv \max_{G^{(i)}} EU \equiv \max_{G^{(i)}} E[G] \tag{4}$$

Thus, a rational building manager will pursue the maximum expected performance.

3.2. Multicriteria decision making

Multi-criteria decision-making problems involve optimal design in the presence of multiple design criteria, typically conflicting each other. In the HDP, we adopt the widely used multi-attribute utility theory (MAUT) [Keeney and Raiffa (1993)] whose aim is the selection of the "best" design alternative from a pool of m preselected alternatives $a^{(1)}, a^{(2)}, \cdots, a^{(m)}$, explicitly known in the beginning of the solution process. The evaluation of the optimal solution is based upon the preferences of the decision maker with respect to a set of performances, or decision criteria $G_1, G_2, \ldots, G_n$ collected in the vector $\mathbf{G}$. The global performance of each alternative depends on all indicators $G_1, G_2, \ldots, G_n$ and it is defined through the multi-attribute utility function $u(\mathbf{G})$. This is expressed as a combination of single attribute utility functions $u_j(G_j)$ of only one performance where the relative importance is defined by weights w_j, $0 \le w_j \le 1$, $\sum_{j=1}^{n} w_j = 1$, of the different performances. Several methods for assigning the weights are discussed in [Wang et al. (2009)]. A simple model of aggregating the attributes is the following linear model

$$u(G_1, G_2, \ldots, G_n) = \sum_{j=1}^{n} w_j u_j(G_j) \tag{5}$$

The schematic of PBE-MAUT is represented in Fig.4

3.3. Predictive risk management for resilient systems

If the decision maker knows if a failure is likely to happen, he/she can plan to prevent it, or to re-

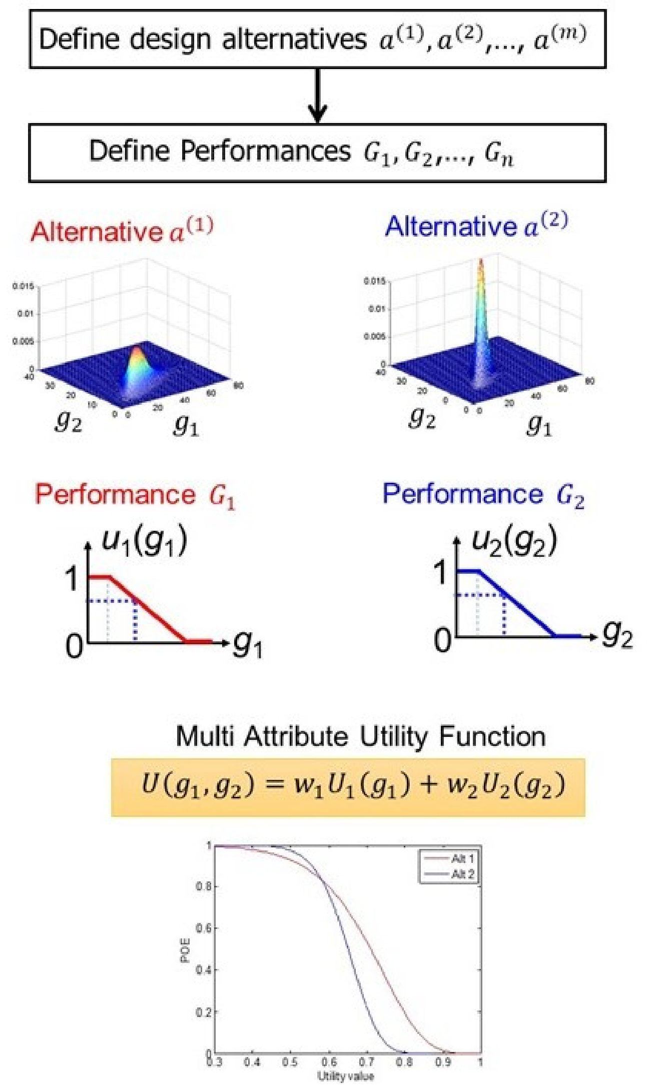

Figure 4: PBE-MAUT

duce its consequences, and to bring back the system to its full functionality in the shortest time possible. To this aim, accurate and confident predictions are needed, so that earlier diagnoses with minimum false alerts can be detected. This because longer detection intervals address better mitigation planning, but only if the alerts can be trusted. In Fig.5 we show a performance, e.g. the damage level. When the performance exceeds a chosen threshold, it is likely that soon a failure may arise. The problem with this approach is the choice of suitable thresholds: typically they are chosen too high (which implies "late alerts" and short reaction time) or too low (too many "false alerts"), see Fig.5(a) and (b), respectively. With the HDP a different approach may be followed, see Fig.5(c): no threshold needs to be chosen, but a dynamic evolution of the performance is analyzed to check the consequences of the actions of the decision maker.

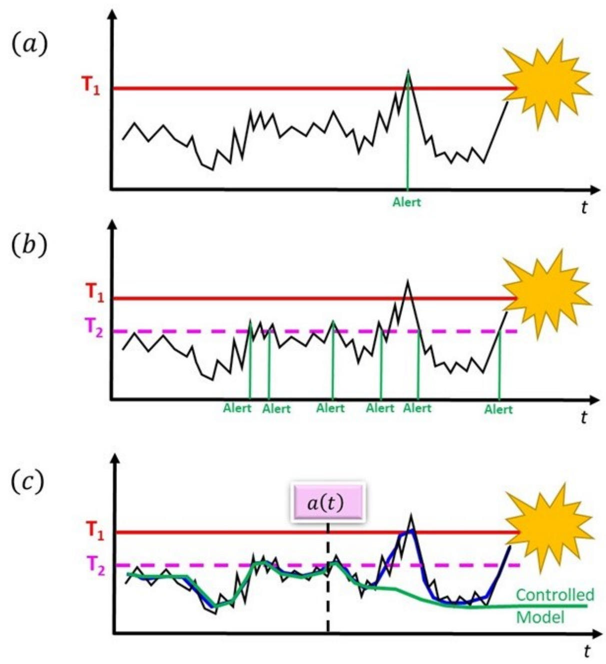

Figure 5: Predictive maintenance

The decision-making process is dynamic in the sense that the optimal decision changes when new information is available. Such dynamic behavior is effectively represented through Bayesian analysis, here modeled through the adoption of Bayesian Networks [Jensen and Nielsen (2007)]. They are adopted because: (*i*) the network can be updated in real time when new information (e.g. from sensors network) is acquired, (*ii*) they are effective in “what-if” scenario capabilities, (*iii*) their transparent modeling allows easy interaction between different stakeholders and decision-makers. The formulation can be used for updating the uncertain input variables, but also the subjective utilities expressing the degree of preference of the decision maker and of the different stakeholders involved in the design process [Alibrandi and Mosalam (2017a); Konstantakopoulos et al. (2018)]. In cases where the scarcity of data makes the probabilistic analysis problematic, the optimal decision may be explored through sensitivity analysis of the decision outcomes to the various input parameters or by combining random and non-probabilistic uncertain parameters [Alibrandi and Koh (2015)].

The framework represents a powerful tool for an extended multi-objective system of management and design under uncertainty. In the BN model of Fig.6, the lifecycle holistic analysis of a system subjected to a hazard is analyzed.

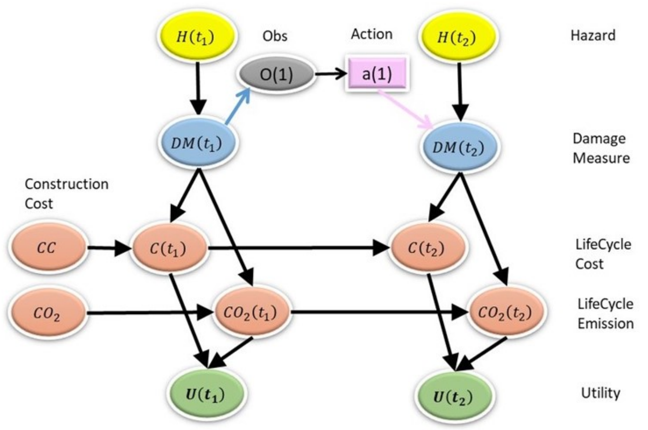

Figure 6: Lifecycle holistic analysis

The performances are the Construction Cost $G_1 \equiv CC$, the Economic Losses $G_2(t) \equiv C(t)$ during the lifecycle, the environmental impact represented by the $G_3 \equiv CO_2$ emission during the construction stage, and $G_4(t) \equiv CO_2(t)$, during the lifecycle. This model can analyze several stochastic processes, including the Damage Measure $DM(t)$, and the utility function $U(t)$. The model can incorporate the degradation of the material. Moreover, it is assumed that, at each year, the decision-maker can choose to develop a plan of maintenance and repair through the action $a(t)$ following the observation $O(t)$. This will affect not only the economic losses $C(t)$, but also the sustainability because of the $CO_2(t)$ emission due to post-hazard repairs. The example shows the strict relationships between sustainability and resilience. The lifecycle actions of the decision-maker will affect the results of the utility function after t years, and accordingly the optimal decision. The conditional probabilities of the BN model may be evaluated through data-driven methods based on the Information Theory [Alibrandi and Mosalam (2017c, 2018a, 2019)] or stochastic equivalent linearization methods [Alibrandi and Mosalam (2017b); Alibrandi and Koh (2017)].

In Fig.7 two different design alternatives of an hypothetical building located in California, Berkeley, are presented. The second option is more resilient but it has a greater construction cost, i.e. $CC^{(2)} > CC^{(1)}$.For details, see Alibrandi and Mosalam (2018b). It is assumed that the building is subjected to earthquake, and that all the damage accumulated inside one year is repaired. It is seen that the total lifecycle cost $C^{(2)}(t_n) < C^{(1)}(t_n)$, with $t_n = 20$ years, because the first optio n requires greater repair and maintenance costs. Interestingly, the lifecycle CO_2 emission of the second design is also less, because of post hazard repairs. This example shows that resilient buildings are sustainable, too.

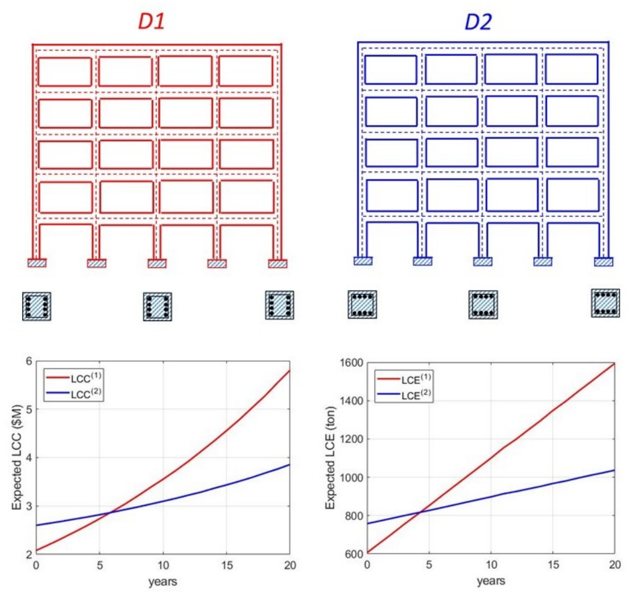

Figure 7: Lifecycle cost and CO_2 emission of two different design alternatives

3.4. *Societal cyber-physical system: human-in-the-loop*

The HDP is an innovative cyber-physical system under uncertainty. A resilient and sustainable design needs to consider the building as a system of subsystems, including soil, foundation, structure, non-structural components (e.g. envelope, HVAC, doors, windows), the HDP can include its most important component: the people.

To this aim, in Konstantakopoulos et al. (2018) we propose a human-centric design driven by the behavior and preferences of the occupants. In particular, in the SinBerBEST office, in Singapore, an experimental setup has been designed, called social game, aimed at incentivizing the occupants to modify their behavior and reducing the overall energy consumption in the office. In the framework, the occupants win points based on how energy efficient is their behavior. The points are used to determine the likelihood of the occupants of winning a prize. To show the effectiveness of the social game, two different alternative are considered: the first one, ranging from 2 May 2017 to 17 October 2017, when the social game is active; the second one, ranging from 2 January 2018 to 1 June 2018, without social game.

In Fig.8 it is shown that the HDP reads from the PI server the data of energy consumption (EC) of a user (panel top left of the figure), for each one of the two alternatives. The module of UQ evaluates the corresponding probability of exceeding of the daily EC of the user, while the module of risk analysis through MCS compares the corresponding expected EC of the user in an year (panel on the bottom right)

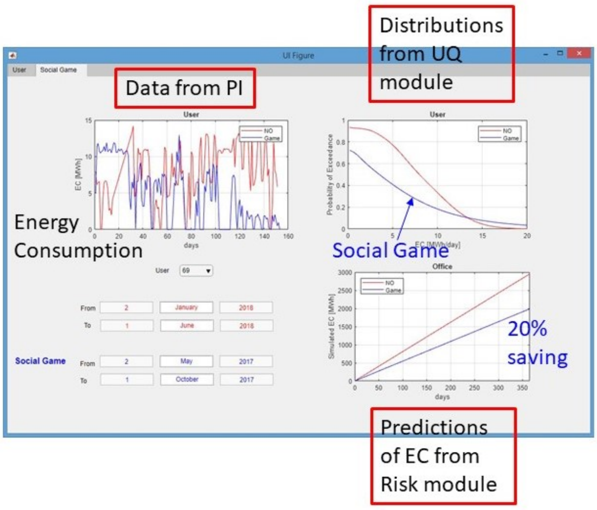

Figure 8: GUI Social Game SinBerBEST

For the user shown in Fig.8, as well as with the community, represented by all the occupants of the office, it is seen that through the incentives it is possible to achieve an energy saving approximately 20%. A major significance of the framework is its capability to derive insights about the behavior of the occupants, and this can be leveraged in designing mechanisms for incentivizing occupants.

4. CONCLUSIONS

In the past decade, there has been an exponential growth in the amount of available data and affordable sensors integrated into the Internet of Things (IoT) as a vital part of our daily life, computing power and high-performance computing, and novel data-driven technologies, such as Machine Learning (ML) and Artificial Intelligence (AI). This is analogous to the changes that occurred in the civil engineering research and practice as a result of the advent of computers, which initiated the Third Industrial Revolution. Currently, we are in the middle of the Fourth Industrial (Digital) Revolution. The in-depth understanding of Computational Intelligence techniques for accurate simulations, together with the availability of data and public resources, promises to accomplish the following new paradigm: *Connect*, *Collect*, *Comprehend*, *Control*, and *Change* making the urban communities more sustainable, resilient and vibrant. The proposed platform, here applied to a building, aims to lead the paradigm shift from the existing notion of Smart City to Resilient Engaged Community where the design and management of the built environment is centered around the humans. It is expected that this novel paradigm will contribute to pursue satisfaction of human needs, enhancing quality of life of the communities and reducing the environmental impact during the entire lifecycle to a level in line with the capacities of our planet.

5. ACKNOWLEDGMENTS

This research was funded by the Republic of Singapore's National Research Foundation through a grant to the Berkeley Education Alliance for Research in Singapore (BEARS) for the Singapore Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) program. BEARS has been established by the University of California, Berkeley, as a center for intellectual excellence in research and education in Singapore. K.M. Mosalam is a core principal investigator of

Tsinghua-Berkeley Shenzhen Institute (TBSI). The authors acknowledge the funding support from SinBerBEST and the partial support from TBSI.

6. REFERENCES

Alibrandi, U. and Koh, C. G. (2015). "First order reliability method in presence of random and interval variables." *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, 1(4).

Alibrandi, U. and Koh, C. G. (2017). "Stochastic dynamic analysis of floating production systems using the first order reliability method and the secant hyperplane method." *Ocean Engineering*, 137, 68–77.

Alibrandi, U. and Mosalam, K. M. (2017a). "A decision support tool for sustainable and resilient building design." *Risk Reliability Analysis Theory and Applications, Springer Series in Reliability Engineering*, 509–36.

Alibrandi, U. and Mosalam, K. M. (2017b). "Equivalent linearization methods for nonlinear stochastic dynamic analysis using linear response surfaces." *Journal of Engineering Mechanics*, 143(8).

Alibrandi, U. and Mosalam, K. M. (2017c). "Kernel density maximum entropy with generalized moments for evaluating probability distributions, including tails, from a small sample of data." *International Journal for Numerical Methods in Engineering*, 113(13), 1904–28.

Alibrandi, U. and Mosalam, K. M. (2018a). "Code-conforming peer performance based earthquake engineering using stochastic dynamic analysis and information theory." *KSCE Journal of Civil Engineering*, 22(3), 1002–15.

Alibrandi, U. and Mosalam, K. M. (2018b). "Lifecycle multi criteria decision analysis using generalized expected utility." *Handbook on Sustainable and Resilient Infrastructure*, ch.39, 762–80.

Alibrandi, U. and Mosalam, K. M. (2019). "Distribution with independent components for uncertainty quantification and structural reliability analysis." *3th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP13*, Seoul, South Korea, May 26–30.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., and Von Winterfeldt, D. (2003). "A framework to quantitatively assess and enhance the seismic resilience of communities." *Earthq. Spectra*, 19(4), 733–752.

Cornell, C. A. and Krawinkler, H. (2000). "Progress and challenges in seismic performance assessment." *PEER Cent News*, 3, 1–4.

Gunay, M. S. and Mosalam, K. M. (2013). "Peer performance-based earthquake engineering methodology, revisited." *Journal of Earthquake Engineering*, 17(6), 829–58.

Jensen, F. V. and Nielsen, T. D. (2007). *Bayesian networks and decision graphs*. Springer Science+Business Media, LLC, New York, 2nd ed. edition.

Keeney, R. and Raiffa, H. (1993). *Decisions with multiple objectives–preferences and value tradeoffs*. Cambridge University Press.

Konstantakopoulos, I., Alibrandi, U., Mosalam, K. M., and Spanos, C. J. (2018). "Hierarchical decision making by leveraging utility theory and game theoretic analysis towards sustainability in building design operation." *6th International Symposium on Reliability Engineering and Risk Management*.

Mosalam, K. M., Alibrandi, U., Lee, H., and Armengou, J. (2018). "Performance based engineering and multi criteria decision analysis for sustainable and resilient building design." *Structural Safety*, 74, 1–13.

NIST (2016). "Community resilience planning guide for buildings and infrastructure systems, volume i & ii." *National Institute of Standards and Technology*.

Von Neumann, J. and Morgenstern, O. (1944). *Theory of Games and Economic Behavior*. Princet. Univ. Press.

Wang, J. J., Jing, Y. Y., Zhang, C. F., and Zhao, J. H. (2009). "Review on multi-criteria decision analysis aid in sustainable energy decision-making." *Renew Sustain Energy Rev*, 13, 2263–78.

WCED (1987). "Our common future." *United Nations World Commission on Environment and Development*.