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Optimal Scheduling of a Self-Healing Building using Hybrid Stochastic-Robust Optimization Approach

Alireza Akbari-Dibavar, Behnam Mohammadi-Ivatloo, *Senior Member, IEEE*, Kazem Zare, and Amjad Anvari-Moghaddam, *Senior Member, IEEE*

***Abstract*—This article provides a two-stage robust energy management method for a self-healing smart building that can handle contingencies that occur during real-time operation. Aside from an electrical link with the distribution network, the smart building is equipped with a diesel generator and photovoltaic solar power generating systems. The energy management system should be smart enough to plan different resources based on the situation. At first, bi-level programming identifies critical faults for affected components based on mean-time-to-repair. After identifying major failures, the faults are described in operational scenarios, and two-stage hybrid robust-stochastic programming technique is used to determine the bid/offer in day-ahead and real-time energy markets, in which stochastic programming is responsible for considering the uncertainty of faults, and the robust optimization approach is used to cope with the uncertainty of real-time market prices. After linearization, the final optimization is modeled as mixed-integer linear programming in GAMS optimization package. For the studied smart building, the daily operational cost is expected to increase from $ 25.794 (for the deterministic case) to $ 28.097 (for the most conservative case) due to the uncertainty of real-time market prices. Due to power shortages caused by the failure of components, the total expected not-supplied load is 6.72 kW (2.53%). A comparison between a naive, and self-healing scheduling indicated that a naive energy management will charge additional $ 2.75 without considering the probability of components failures under the deterministic case.**

***Index Terms*— Smart building, resiliency-oriented scheduling, two-stage stochastic programming, self-healing, bilevel problem.**

NOMENCLATURE

Symbols	***Definition***
t	Index of time (Hour)
s_i	Index of failure scenarios
ρ_s	The probability of scenarios
D_t^e	Hourly electric demand (kW)
$MTTR^i$	The mean-time-to-repair of component *i* (Hour)
$\overline{S}$	Maximum exchangeable power with the market (kW)
$Voll$	Value of lost load ($/kWh)
$\overline{P}_t^{PV}$	Maximum PV generation at time *t* (kW)
P_t^{PV}	Generated power by PV (kW)
P_t^{DA}, $P_{t,s}^{RT}$	Exchanged powers in day-ahead and real-time markets (kW)
$P_{t,s}^{dis}$	Generated power by diesel generator (kW)
$Lsh_{t,s}$	Curtailed load (kW)
u_t^i, z_t^i	Binary variables equal to 1 when component *i* is out-of-service
λ_t^{DA}, λ_t^{RT}	Day-ahead and real-time market prices ($/kWh)
λ^{dis}	Generation cost of diesel generator ($/kW)
γ_s^1, γ_s^2, γ_s^3	Parameters indicating the availability of line, diesel generator and photovoltaic, respectively.
x_t^1, x_t^2	Auxiliary continuous positive variables
ξ_t^1, ξ_t^2, ψ_t^1, ψ_t^2	Special ordered set variables

I. INTRODUCTION

WITH the development of renewable resources, the use of these technologies is increased by end-users, which opened a way for the active entry of residential and commercial sectors in the electricity markets. However, without constructing an efficient energy management system, economic losses will be incurred due to numerous uncertain factors in the energy management process. The researchers in the search for solving the issue have proposed different concepts, methods and strategies for active buildings to reduce their energy consumption, and successfully participate in the electricity markets, and gain financial benefits. For instance, a smart home energy management framework is constructed by [1], which takes the help of optimal scheduling of flexible demands, plug-in electric vehicles (EV) and battery storage (BS) to maximize the utilization of renewable energies and provide demand response services to the utility grid. The optimal utilization of renewable energies besides satisfying thermal comfort is targeted by [2]. The authors constructed an optimization model to minimize the energy cost by scheduling different loads and exchanging power with the grid. With the help of the building's thermal capacity, the required BS capacity is minimized. The thermal

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and electrical consumption management of smart homes is studied in [3], considering the effects of ambient temperature on thermal energy requirements under energy price uncertainty. The energy consumption minimization using demand response programs (DRP) is addressed in [4], by considering various loads and comfort indexes of inhabitants in a smart home. In another work [5], the authors evaluated the effects of several DRP, including time-of-use, real-time pricing, and inclining block rate, on optimal energy management of a residential home in the presence of photovoltaic (PV), BS, and exchanging power with electric network. The participation of a residential building in the power market is carefully carried out in [6] by modeling electric and thermal loads, PV, and storage systems. The presented model results in optimal bidding curves that should be submitted to the electric market, taking into account the uncertainty of PV generation and market prices using interval-based stochastic programming. In [7], the self-scheduling problem of a smart home is surveyed with more concentration on uncertainty management. In this paper, the market participation of a price-taker residential user is assessed by a hybrid robust-stochastic approach to cover the uncertainties of both day-ahead and real-time markets' prices and PV generation. The energy scheduling problem of a data center building is investigated by [8]. The authors integrated the combined cooling, heat and power units and BS to provide flexibility to the scheduling problem. The market participation in day-ahead and real-time markets is inspected by formulating a two-stage framework. Also, two-stage stochastic programming (SP) is conducted in [9]. The authors have modeled the participation of a smart home in spot markets, contractual agreements, and gaining power from renewable resources considering the uncertainties of resource generation, market price, and availability of non-controllable loads employing a set of scenarios.

A. Resiliency-based energy management

The resiliency in power and energy systems is introduced as the capability of the system to foresee and withstand hazards and return to normal operation after the events with the least cost. According to [10], smart grids are vulnerable to cyber-physical attacks and social crimes. As the heart of the smart grids, smart home energy management plays a critical role in society and the energy sector. Additionally, the need for resilient smart buildings with electricity generating capacity stems from the fact that home medical equipment is vulnerable, and a power outage has unpleasant consequences. Extreme event causing power outages is a danger to domestic energy management systems [11]. The resiliency-oriented energy management for small-scale energy systems, such as microgrids and nano-grids has been focused on in recent years. For instance, resiliency-oriented scheduling of a microgrid including PV and BS is assessed by [12]. The microgrid is designed to supply a commercial building in islanded mode during extreme events. The authors of [13] argued about increasing the resiliency level for smart homes using optimally sized PV and BS facilities. This paper also provides an optimal control strategy based on model predictive control to make the decision on the real-time operation. For some predefined grid outages, the authors of [14] proposed an energy management scheme for the residential buildings, in which plug-in hybrid EVs and PV are considered as backup power resources. Stochastic programming is used to model the uncertainty of PV's power generation.

The peer-to-peer (P2P) method and system-of-system (SOS) architecture can be used to improve robustness in communities. In these modes, numerous buildings with different power generation technologies pool their resources in times of need, such as when components fail. In this regard, the authors of [15] proposed a P2P framework for energy management of three residences, two of which are solar-powered and one of which is powered by a hydrogen system (HS). The challenge is to determine the optimal sizes for PV, HS, and power lines connecting dwellings in order to save operating costs. Stochastic programming is used to expect the uncertainty of solar output and load consumption in the optimization context.

They provide a peer-to-peer framework for energy management of three residences, two of which are solar-powered and one of which is powered by hydrogen (HS). The challenge is to determine the best sizes for PV, HS, and power lines connecting dwellings in order to save operating costs. Furthermore, stochastic programming is used to predict the uncertainty of solar output and load consumption. A shared parking station was employed in a P2P approach to improve the resiliency of two residential and commercial buildings in [16]. With the use of EVs and load-adjustment strategies, the energy cost of the system considering random power outages with various duration has been minimized. However, the uncertainties are not addressed. SOS-based operation is prescribed by [17] for energy and water management of a residential complex. The buildings within the complex share their resources during logjams, for example, utility disconnection, to feed electric loads and water desalination units. The uncertainties with renewable resources are handled by the robust optimization approach (ROA).

A self-healing system is one that is capable of intelligently recognizing, finding, and evaluating defects in a timely manner, as well as taking appropriate remedial activities to quickly return to normal situation. To provide self-healing features, contemporary fault detecting modules, smart meters, and communication infrastructures are required [18]. Self-healing energy management is a relatively novel topic that is widely focused on smart grids and buildings in recent publications. In [19], considering the capacity withholding of power generation facilities, two-stage energy management is offered for a self-healing distribution network. While the regular operation is assumed for the day-ahead stage, effects of the external events are imposed in real-time process. The uncertainty associated with EVs, renewable power generation and energy prices is considered by scenario-based stochastic programming but the uncertainty of faults has not been involved. The authors of [20] make levels a DC microgrid with a green building and propose a multi-agent control scheme for developing self-healing functions for a building with PV, BS and supercapacitor (SC), which is connected to a DC grid to supply DC loads directly

and AC loads through DC-AC converters. It should be noted that the uncertainties associated with normal and faulty operation have not been evaluated. The critical point with this work is to compare a microgrid with a smart building. Hence, a smart building can be referred to as a nano-grid, and self-healing functions can be assessed similarly with smart grids. However, the works focusing on self-healing smart buildings are a handful. In this mean, the autonomous energy management of a building without extra resources is interesting. With this respect, a self-healing energy management plan for a smart home is prescribed in [21] by coordinating the operation of wind power generation (WPG), DRP, diesel generator (DG), and vehicle-to-home capacity in the off-grid operation to minimize the energy cost. Stochastic programming is applied to model the uncertainties of WPG and load consumption. The resiliency of a self-healing building in off-grid and grid-connected modes is addressed in [22]. The BS reserve, EVs, and PV systems create a resilient energy management scheme leading to minimum energy cost. The PV generation uncertainty is modeled by scenario-based stochastic programming. In [23], the author provided an optimization framework for evaluating the effects of resiliency and uncertainty on the energy management problem of a typical building powered by PV and BS connected to the utility grid. The operation is tested on a 90-day time horizon to investigate the energy and resiliency costs considering the uncertainties of load consumption, PV generation, and energy prices using stochastic programming. Finally, a design framework is developed in [24]. The target is to address the planning problem of a self-healing building incorporating a PV system, DG, and BS connected to an electric grid considering the energy efficiency and resiliency criteria. Optimal designing parameters, such as nominal capacity of resources are obtained, where the yearly not-supplied load is minimized.

The reliability of a self-healing building depends on the successful operation of each involved component, because it influences the strategy of market participation and consequently affects the economic and resiliency aspects. Furthermore, the uncertainty associated with natural and human-made disruptions should be integrated with optimal energy management to reduce the risks and probable losses [25].

B. Novelty and contributions

This paper is the extended version of the previous conference paper [26], in which a bi-level model for detecting the vulnerabilities of a self-healing building was proposed and used for failure scenarios generation in day-time operation. In this version, the self-healing strategy is compared with a naive energy management strategy to reveal the benefits of detecting faults before real-time operation and accordingly recommendations for resiliency enhancement are deliberated. As presented in [26], the case study is a residential building equipped with a DG and PV solar system. The grid connection makes it possible to balance the generation and consumption and take advantage of market participation. By deriving optimal biding/offering strategy in day-ahead and real-time markets and using the optimal commitment of PV and DG, the self-healing building encounters critical disruptions with the lowest load curtailment, assuring the minimum operation cost. Moreover, the robust optimization approach is proposed to manage the uncertainty of real-time market price. To highlight the novelties, it is decided to compare the related works with the presented paper in Table I.

TABLE I
COMPARISON BETWEEN SIMILAR WORKS

Ref.	Problem structure	Critical faults detection	Fault uncertainty modeling	Operation uncertainty modeling	Items
[12]	LP	No	No	Price/PV (CVaR)	PV/ BS
[13]	MILP	No	No	No	PV/ BS
[14]	MILP	No	No	PV (SP)	PV/ EV
[15]	LP	No	No	PV/load (SP)	PV/ HS/ P2P
[16]	MILP	No	No	No	EV/ P2P
[17]	MILP	No	No	Renewable power (RO)	WPG/ PV/ BS/ DG/ DRP SOS
[19]	MINLP	Yes (Simulation-based)	No	EV/price/ load/WPG/ PV (SP)	WPG/ PV/ BS/ EV/ DG
[20]	Multi-agent controller	Yes (Simulation-based)	No	No	PV/ BS/ SC
[21]	MILP	Yes (N-1 criterion)	No	WPG/ load/ price (SP)	EV/ WPG/ DG/ DRP
[22]	MILP	No	No	PV (SP)	EV/ BS/ SC/ PV
[23]	MILP	No	SP	PV/load/ price (SP)	PV/ BS
[24]	MILP	Yes (N-1 criterion)	No	No	PV/ BS/ DG
This paper	MILP	Yes (Bi-level)	SP	Real-time price (ROA)	PV/ DG

Based on the comparison presented in Table I, this paper is the first that proactively schedules a smart self-healing building by detecting severe failures in real-time operation, and based on this anticipation, creates uncertainty-based scheduling that integrates the failure rate of the components to consider the importance of each failure. While some of the previous works, such as [19]–[21] and [24], have detected the critical faults in their work, these are based on complete simulation or using (N-1) criterion that is not efficient from viewpoint of computational time. In turn, we proposed bi-level programming to find the critical faults and generate a set of operational scenarios. The

proposed bi-level programming is reformulated as mixed-integer linear programming, which is efficient and timely. From Table I, Ref. [23] modeled the uncertainty of faults and outages using SP, which is seen in this paper similarly. For operational uncertainty, the real-time price uncertainty is handled by the ROA, which is proved to be efficient for severe uncertainty modeling. At the same time, other works have used pure SP or conditional value-at-risk (CVaR) that needs a vast data set for prediction. For a realistic case, a smart building may not be equipped with numerous flexible resources. The smart building in this paper, includes necessary electricity generation facility and backup resources.

The organization of the paper is as follows. The problem formulation is presented in Section III. The case study descriptions and numerical evaluations are reported in Section IV. The conclusions are expressed in Section V.

III. PROBLEM FORMULATION

The complete procedure of the proposed self-healing energy management of the building consists of two phases. The first phase is constructed as bi-level programming, which determines the drastic failures leading to high operating costs. In the second phase, which directly determines the operation strategy, the two-stage stochastic programming finds the optimal bids/offers in day-ahead and real-time markets. To manage the uncertainty of the problem due to the fluctuations of real-time market price, the robust optimization approach with different conservation levels is investigated.

A. Diagnosing critical faults

As mentioned before, the self-healing system should anticipate the failure of components and their effects on overall performance and adopt proper actions. One way to identify the critical failure is what has been done in previous works, such as considering all the possible faults, and effects of failures on the system operation, incurred costs and curtailed load. However, for a complex energy system with numerous involved components and considering the sequence and various permutations of faults, this strategy cannot be used. Moreover, in this strategy, all the possible failures are evaluated while only some of them are challenging in nature. One promotable approach to find the vulnerable part of an energy system is to use bi-level programming. At the upper-level, the manager tends to enforce severe failures on system, and at the lower-level, he/she tries to keep the system security. In other words, the attacker-defender problem is adopted in this paper from the viewpoint of the decision-makers to find the weak points of the self-healing smart building. However, this is done by considering the MTTR and overlapping of failures of component that have not been done before due to authors' knowledge. In this process, the upper-level problem is responsible for creating a challenging condition for system by proposing the time and type of component failure (similar to an attacker). In contrast, the lower-level problem is responsible for system balance and security to minimize the overall cost and restore critical loads during faults (similar to a defender). More detailed information is provided in the following subsections. By using a bi-level programming, the challenging situations can be found intelligently and efficiently.

B. The upper-level problem

At the upper-level, the objective is to maximize the system cost (including the penalty of curtailed load) by determining some binary variables that indicate the failure of each component. This stage models the behavior of an attacker tries to remove components and impose more cost and load disruption. This is not limited to a provocative action; the failure of components is commonplace in realistic cases. The objective function is shown in (1) that consists of two main parts. The first item is cost related to power exchanged with the network in the day-ahead market, and the second item calculates the cost in real-time operation. The upper-level problem is solved subject to sequence and continuity of faults. That means, if a fault has occurred, the component is not available during maintenance time or MTTR. Constraints (2) and (3) model the sequence and continuity of faults. Constraint (4) assures that each component's outage time equals the MTTR. Decision variables of this level are binary variables indicating components' status.

$$\underset{u,z}{Max} \quad [\sum_{t=1}^{T} P_t^{DA} \times \lambda_t^{DA}] + [\sum_{t=1}^{T} (P_t^{RT} \times \lambda_t^{RT}) + (P_t^{dis} \times \lambda^{dis}) + (Lsh_t \times Voll)] \tag{1}$$

$$\sum_{t'=t}^{t+MTTR-1} u_{t'}^{i} \geq MTTR \times z_t^{i} \tag{2}$$

$$z_t^{i} \geq u_t^{i} - u_{t-1}^{i} \tag{3}$$

$$\sum_{t=1}^{T} u_t^{i} = MTTR \tag{4}$$

C. The lower-level problem

The lower-level problem models the behavior of the defender or system operator that tries to crisis management with the minimum cost assuring the system balance. The system cost is minimized in the lower-level, according to (5), subject to energy balancing constraint in (6), and components' availability constraints (7)-(10). Equations (7) and (8) limit the exchanged power with grid in day-ahead and real-time markets, respectively. However, by the disconnection of line in real-time operation, the building will not be able to fulfill the contracts of day-ahead market too. Equations (9) and (10) represent the allowable power generation by PV and DG, respectively. The maximum load shedding amount is limited in (11). The decision variables of the upper-level (i.e., binary variables) are treated as input parameters in the lower-level problem indicated in (7)-(11). Hence, the complete bi-level problem not only simulates the critical failures, but also encounters them with proper decision making. Dual variables (i.e., the Lagrange multipliers) of the constraints of lower-level problem are defined in front of each one that will be used to reformulate the bi-level problem.

$$\underset{P_t^{DA}, P_t^{RT}, P_t^{dis}, Lsh_t, P_t^{PV}}{Min} \quad [\sum_{t=1}^{T} P_t^{DA} \times \lambda_t^{DA}] + [\sum_{t=1}^{T} (P_t^{RT} \times \lambda_t^{RT}) + (P_t^{dis} \times \lambda^{dis}) + (Lsh_t \times Voll)] \tag{5}$$

$$P_t^{DA} + P_t^{RT} + P_t^{dis} + Lsh_t + P_t^{PV} - D_t^{e} = 0, (\phi_t) \tag{6}$$

$$-\bar{S}\times(1-u_t^1)\le P_t^{DA}\le \bar{S}\times(1-u_t^1),(\alpha_t^{\min},\alpha_t^{\max}) \quad (7)$$

$$-\bar{S}\times(1-u_t^1)\le P_t^{RT}\le \bar{S}\times(1-u_t^1),(\beta_t^{\min},\beta_t^{\max}) \quad (8)$$

$$0\le P_t^{dis}\le \bar{P}^{dis}\times(1-u_t^2),(\delta_t^{\min},\delta_t^{\max}) \quad (9)$$

$$0\le P_t^{PV}\le \bar{P}_t^{PV}\times(1-u_t^3),(\nu_t^{\min},\nu_t^{\max}) \quad (10)$$

$$0\le Lsh_t\le D_t^e,(\mu_t^{\min},\mu_t^{\max}) \quad (11)$$

D. Reformulation of bi-level programming

The conventional method for solving bi-level problems is to recast it as a single-level problem by implementing Karush-Kuhn-Tucker (KKT) conditions on the lower-level problem. The final single-level problem is represented by the equations (12)-(27), including feasibility constraints (15)-(19) and complementarity slackness conditions for inequality constraints as defined in (20)-(27).

$$\underset{u,z}{Max} \quad [\sum_{t=1}^{T}P_t^{DA}\times\lambda_t^{DA}]+ [\sum_{t=1}^{T}(P_t^{RT}\times\lambda_t^{RT})+(P_t^{dis}\times\lambda^{dis})+(Lsh_t\times Voll)] \quad (12)$$

Constraints (2)-(4) (13)

Constraints (6)-(11) (14)

$$\lambda_t^{DA}-\phi_t+\alpha_t^{\max}-\alpha_t^{\min}=0 \quad (15)$$

$$\lambda_t^{RT}-\phi_t+\beta_t^{\max}-\beta_t^{\min}=0 \quad (16)$$

$$\lambda^{dis}-\phi_t+\delta_t^{\max}-\delta_t^{\min}=0 \quad (17)$$

$$-\phi_t+\nu_t^{\max}-\nu_t^{\min}=0 \quad (18)$$

$$Voll-\phi_t+\mu_t^{\max}-\mu_t^{\min}=0 \quad (19)$$

$$0\le(P_t^{DA}+\bar{S}\times(1-u_t^1))\perp\alpha_t^{\min}\ge 0 \quad (20)$$

$$0\le(\bar{S}\times(1-u_t^1)-P_t^{DA})\perp\alpha_t^{\max}\ge 0 \quad (21)$$

$$0\le(P_t^{RT}+\bar{S}\times(1-u_t^1))\perp\beta_t^{\min}\ge 0 \quad (20)$$

$$0\le(\bar{S}\times(1-u_t^1)-P_t^{RT})\perp\beta_t^{\max}\ge 0 \quad (21)$$

$$0\le P_t^{dis}\perp\delta_t^{\min}\ge 0 \quad (22)$$

$$0\le\bar{P}^{dis}\times(1-u_t^2)-P_t^{dis}\perp\delta_t^{\max}\ge 0 \quad (23)$$

$$0\le P_t^{PV}\perp\nu_t^{\min}\ge 0 \quad (24)$$

$$0\le\bar{P}_t^{PV}\times(1-u_t^3)-P_t^{PV}\perp\nu_t^{\max}\ge 0 \quad (25)$$

$$0\le Lsh_t\perp\mu_t^{\min}\ge 0 \quad (26)$$

$$0\le(D_t^e-Lsh_t)\perp\mu_t^{\max}\ge 0 \quad (27)$$

E. Linearization of resulted single-level problem

The initial bi-level problem was mixed-integer linear programming. However, after applying the KKT conditions, non-linear constraints in the form $0\le a\perp b\ge 0$ complicate the solution procedure. These constraints are linearized by employing Schur's decomposition method and the help of special ordered set of variables type 1 (SOS1). More information regarding the linearization techniques for such constraints could be found in [27]. Constraints (20) and (21) are linearized in (28)-(33), for example, and the rest of the constraints can be linearized in the same manner.

$$x_t^1-(\xi_t^1+\xi_t^2)=0 \quad (28)$$

$$x_t^1=\frac{P_t^{DA}+[\bar{S}\times(1-u_t^1)]+\alpha_t^{\min}}{2} \quad (29)$$

$$\xi_t^1-\xi_t^2=\frac{P_t^{DA}+[\bar{S}\times(1-u_t^1)]-\alpha_t^{\min}}{2} \quad (30)$$

$$x_t^2-(\psi_t^1+\psi_t^2)=0 \quad (31)$$

$$x_t^2=\frac{[\bar{S}\times(1-u_t^1)]-P_t^{DA}+\alpha_t^{\max}}{2} \quad (32)$$

$$\psi_t^1-\psi_t^2=\frac{[\bar{S}\times(1-u_t^1)]-P_t^{DA}-\alpha_t^{\max}}{2} \quad (33)$$

The SOS1 variables are treated as integer variables by most of the solvers. Hence, the bilevel programming (1)-(11), can be modeled as a mixed-integer linear programming (12)-(19) and linearized forms of complementarity slackness conditions with high accuracy and computational efficiency are presented.

F. Two-stage energy management of the building

The self-healing energy management problem is assessed in this section. The problem is formulated as two-stage stochastic programming involving the risk of component failures and their probability. The scenarios of failures are generated based on bi-level problem results in the previous section. The proposed two-stage programming determines the optimal bids/offers of the building in day-ahead and real-time markets and the energy management scheme to achieve the minimum operation cost. The bids/offers are derived based on forecasts of the day-ahead and real-time markets' prices. Although relatively accurate forecasting can be assumed for day-ahead market price, the real-time market price is highly volatile. To address the uncertainty of it, the robust optimization approach is exploited by defining a confidence interval on the real-time market price, which covers a wide range of deviations. An explanation of robust approach background for price uncertainty management can be found in [7].

In the following, the two-stage stochastic programming is formulated. The objective function of this phase is to minimize the operation cost and load curtailment economic losses, shown in (34). The decision variables of the day-ahead stage should be scenario-free since the failures occurred in real-time operation, and the second stage is responsible for considering them according to predefined scenarios. The maximum power exchanged in the day-ahead market is limited in (35). As shown, the availability of each component in real-time operation is modeled by constants in (36)-(39). The presented formulation is risk-neutral without considering the effects of uncertainty of real-time market price.

$$\underset{P_t^{DA},P_t^{RT},P_t^{dis},Lsh_t,P_t^{PV}}{Min} [\sum_{t=1}^{T}P_t^{DA}\times\lambda_t^{DA}]+ [\sum_{t=1}^{T}\sum_{s=1}^{N_s}\rho_s\{(P_{t,s}^{RT}\times\lambda_t^{RT})+(P_{t,s}^{dis}\times\lambda^{dis})+(Lsh_{t,s}\times Voll)\}] \quad (34)$$

$$-\bar{S}\le P_t^{DA}\le\bar{S} \quad (35)$$

$$-\bar{S}\times\gamma_s^1\le P_{t,s}^{RT}\le\bar{S}\times\gamma_s^1 \quad (36)$$

$$0\le P_{t,s}^{dis}\le\bar{P}^{dis}\times\gamma_s^2 \quad (37)$$

$$0\le P_{t,s}^{PV}\le\bar{P}_t^{PV}\times\gamma_s^3 \quad (38)$$

$$0 \le Lsh_{t,s} \le D_t^e \quad (39)$$

In order to intervene in the effects of real-time market price uncertainty on the operation problem, the risk-neutral problem is updated as follows. $q(t), y(t), Z_0$ are auxiliary variables of the robust optimization approach. Γ adjusts the conservation level, a positive constant between 0 and 1.

$$Min \quad [\sum_{t=1}^{T} P_t^{DA} \times \lambda_t^{DA}] + Z_0 \times \Gamma + \sum_{t=1}^{T} q(t)$$
$$[\sum_{t=1}^{T} \sum_{s=1}^{N_s} \rho_s \{(P_{t,s}^{RT} \times \lambda_t^{RT}) + (P_{t,s}^{dis} \times \lambda^{dis}) + (Lsh_{t,s} \times Voll)\}] \quad (40)$$

Constraints (35)-(39) (41)

$$Z_0 + q(t) \ge (\overline{\lambda}_t^{RT} - \underline{\lambda}_t^{RT}) \times y(t) \quad (42)$$

$$y(t) \ge P_{t,s}^{RT} \quad (43)$$

$$q(t), y(t), Z_0 \ge 0 \quad (44)$$

The proposed optimization (40)-(44) is a two-stage hybrid stochastic-robust model that leads to resiliency-oriented scheduling of the building considering the possibility of equipment faults, MTTR, and the uncertainty of energy price in real-time market.

IV. NUMERICAL EVOLUTIONS

A. Case Study

The studied residential building is a smart energy nano-grid that interactively takes part in the local energy market. By means of the PV and DG, the building enhances the self-healing attributes. Fig. 1 shows the structure of the studied residential building. Due to the very high investment cost and high depreciation of BS that eventually leads to a sharp increase in operating costs, the operation of the residential building is investigated in the absence of BS. However, component failures challenge efficient and resilient operations. Without considering the impacts of such failures on the energy management issue, the inhabitants will suffer from economic losses besides power outages.

The failure rates and required time for repair of each component (MTTR) are involved in the energy management problem. The failure rates of the PV system, DG, and network line are assumed to be 40%, 30%, and 20%, respectively, in a sample day to magnify the harmful impacts of component failure on the energy management problem and investigate the performance of the proposed model. The required times for repair of the PV system, DG, and network line reconnection are assumed to be 3, 3, and 5 hours, respectively. Table II represents the faults scenarios that are created based on results of bi-level programming in section III. Scenario #1 stands for the normal condition. The probability of each scenario is dependent on the amount of failure rate. For example, for scenario #8, where all of the components are out of service, the probability is calculated as (0.4×0.3×0.2). The faults occur in times represented by Table III. Fig. 2 illustrates the data used in the simulation. The generation cost of a DG with a nominal capacity of 14 kW is set to 0.3 $/kW. The maximum exchangeable power with day-ahead and real-time markets is 20 kW for each market. The value of the lost load (VOLL) is assumed 1 $/kW. Some of the input data are adopted from [24] while some of them are assumed known and unique for this paper.

Fig. 1. Schematic of self-healing building.

TABLE II
FAILURE SCENARIOS

	S1	S2	S3	S4	S5	S6	S7	S8
PV	1	0	1	1	0	0	1	0
DG	1	1	0	1	0	1	0	0
Line	1	1	1	0	1	0	0	0
Probability of scenarios	0.336	0.224	0.144	0.084	0.096	0.056	0.036	0.024

TABLE III
FAILURE TIMES

	S1	S2	S3	S4	S5	S6	S7	S8
PV	NaN	14-16	NaN	NaN	14-16	14-16	NaN	14-16
DG	NaN	NaN	19-21	NaN	19-21	NaN	20-22	21-23
Line	NaN	NaN	NaN	20-24	NaN	20-24	20-24	20-24

B. Simulation results

The results are found by solving the proposed optimization models in GAMS optimization software using CPLEX solver. Due to the linear feature of the proposed optimization models, the results are optimal. As mentioned, the building takes part in the day-ahead market to buy/sell energy, in which the bids/offers are submitted one day before the real-time operation. During real-time operation, it is possible to balance the generation-consumption more accurately according to failure occurrences. The deviation between day-ahead and real-time market prices makes an opportunity to gain more economic benefits.

The proposed robust optimization provides different strategies for risk-neutral and risk-averse decision-makers. Without considering the uncertainty of real-time price, the decisions are made according to the forecasted amount of real-time prices. However, the risk-averse decision maker is interested in evaluating the cost with considering the effects of severe uncertainty to obtain the lowest risk. Although the bids/offers in the day-ahead market are determined independent

of failure scenarios, they depend on the decision-maker strategy. The decision variables of the day-ahead stage are reputed as here-and-now variables. While the decision variables in the real-time market are referred to as wait-and-see variables. Fig. 3 depicts the self-scheduling of a residential building in the day-ahead market. The residential building can buy or sell the energy each time, respectively, shown by positive and negative amounts in Fig. 3. Due to lower energy prices in the day-ahead market, the residential building tends to buy power from the market with the maximum allowable capacity the majority of the time. In addition, the deviation of energy prices between day-ahead and real-time markets and the surpassing power of PV system and DG makes it available to sell power at times 3, 5, 6, and 10 p.m. Moreover, the differences between risk-neutral and risk-averse decision-makers are evident in Fig. 3.

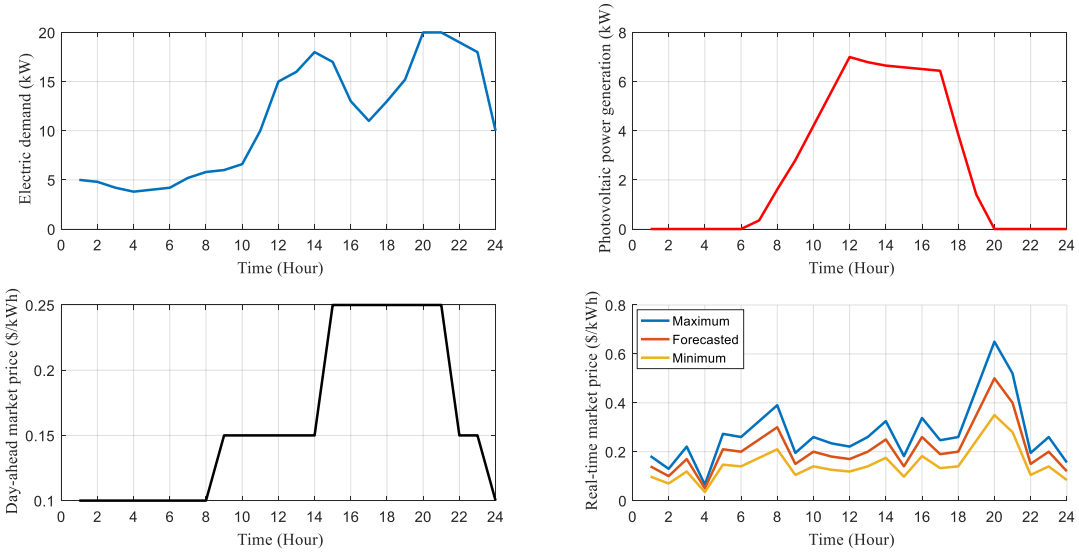

Fig. 2. The estimations of electric demand, PV generation, day-ahead market price, real-time market price and corresponding confidence interval.

Due to lower energy prices in the day-ahead market, the building buys power from the market with the maximum allowable capacity most of the time. In addition, the deviation of energy prices between day-ahead, and real-time markets and the excess power generated by the PV system makes it available to sell power at times 3, 5, 6 and 10 p.m. Different scheduling plan is obtained for risk-neutral, and risk-averse decision-makers as shown in Fig. 3.

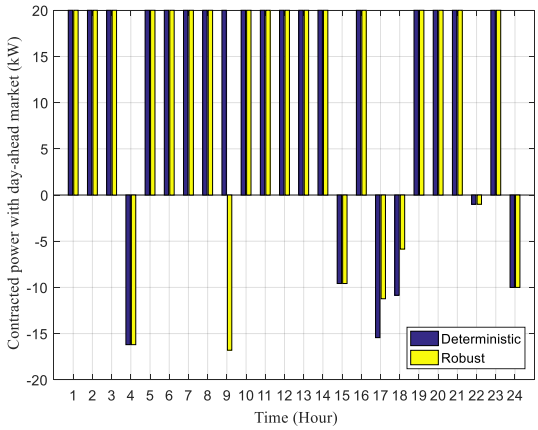

Fig. 3. Exchanged power in the day-ahead stage.

TABLE IV

OPERATION COST VERSUS BUDGET OF UNCERTAINTY

Γ	0	0.2	0.4	0.6	0.8	1
Cost ($)	25.794	26.274	26.754	27.212	27.668	28.097

The energy balance in the system is held under real-time operation. It is necessary to take different energy management plans according to failures directed by scenarios. The exchanged power with the network in real-time operation is plotted in Fig. 4. According to Fig. 4, the residential building acts as a seller in the majority of the time in the real-time market due to relatively higher prices. The building cannot sell/buy energy to/from the energy market under scenarios #4,#6,#7 and #8 at time slots 8 to 12 p.m. because the connection line is out-of-service according to Tables II and III. In these conditions, the purchasing power from the day-ahead market is not accessible and leads to economic losses, which are seen in the proposed model. At the time of disconnection, the loads are fed by DG, if it is available, and the exceeded load consumption is curtailed. Moreover, consideration of price uncertainty changed the decision plan in the real-time market, as well. For instance, at 8 a.m., 9 a.m., 5 p.m., and 6 p.m.

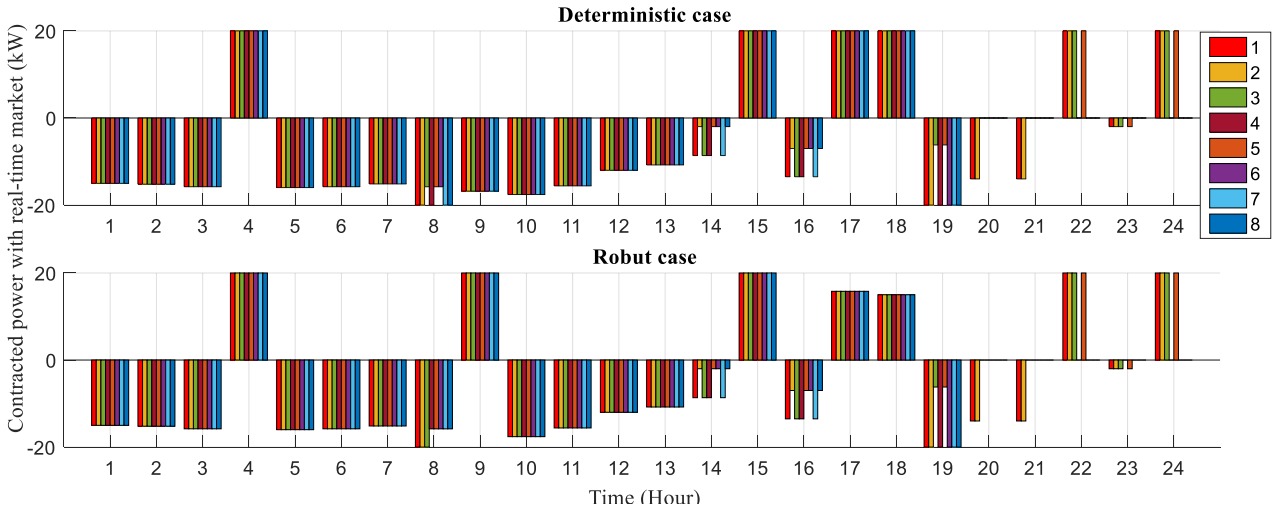

Fig. 4. Exchanged power in the real-time stage.

The most troublesome condition of the building energy management is related to line outage that occurred under scenarios #4, #6, #7, and 8# during 8 to 12 p.m. In Fig .5, the amount of curtailed load and actual load are compared. The load shedding in 8 to 11 p.m. is unavoidable since all resources are out-of-service. However, an optimal energy management plan reduces the amount of curtailed load due to its look-ahead feature. According to failure scenarios, the total expected not supplied load is 6.72 kW or 2.53% in the daytime operation. It should be emphasized that the disruptions considered in this paper are the worst ones provided based on the vulnerability assessment of the building in section III. Finally, Table IV represents the operation cost of building considering the different budgets of the uncertainty of real-time price. The cost corresponding to Γ=0 is related to risk-neutral strategy calculated based on forecasted amounts of the real-time market price. By increasing the conservatism level, the operation cost increases show that the decision-maker pays more to enhance robustness. Γ=1 captures the whole uncertainty budgets and reveals that operation cost will exceed $ 28.097 within the confidence interval defined for the real-time price.

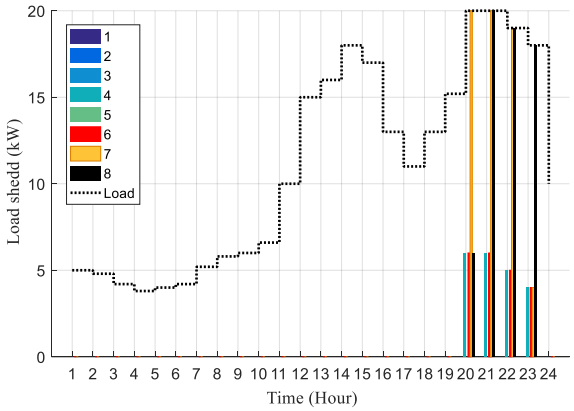

Fig. 5. Comparison between actual and curtailed loads.

C. Discussion

The methodology proposed in this paper can schedule a self-healing smart building by anticipating drastic failures considering the time of repair. In fact, it prevents reckless actions done by a naive decision-maker. The proposed approach is scalable and can be implemented for large-scale applications such as multi-carrier energy systems in industrial parks. The computational cost of the proposed method is efficient enough to be implemented during daily operation. This can be beneficial for systems with model predictive controllers to foresee the system's state and provides look-ahead controlling signals. For the current problem, the initialization phase, which creates eight operational scenarios, takes about 40 seconds and the energy management phase takes about 7 sec while conservation parameter covers from Γ=0 to Γ=1 using a laptop with Intel Pentium Gold CPU and 4 GB of Ram. It should be noted that the operational scenarios increase by the numbers of components and can increase the computation time in larger cases. Another important discussion is about the accuracy of input data, in particular, the mean-time-to-repair and failure rate of components. It should be noted that the equipment such as PV, DG and line has a minimal failure rate per year and their MTTR depends on the intensity of the failure. Accordingly, to have a practical comparison among the self-healing and naive energy management strategies, the failure rate, and MTTR are selected exaggerated and this does not restrict the ability of methodology in reality. Table V shows a fair comparison among naive and self-healing energy management strategies for the studied smart building using forecasted real-time prices (i.e., Γ=0). It is notable that naive energy management schedules the day-ahead and real-time bids/offers without considering the failures, and encounters with failure during real-time operation.

It could also be clearly understood from Table V that by considering the probability of failures of components in daily operation, the expected cost can be reduced by $ 2.75 (10%). This also decreases the probability of load shedding when corrective strategies are taken into account (for example, P2P

contracts or SOS operation) or when additional equipment such as energy storage has been installed. While the naive scheduling tries to minimize the overall cost, it takes a different strategy from the self-healing strategy leading to relatively higher costs in day-ahead market. It compensates for the higher cost of the day-ahead market through real-time trades that is true only in scenario #1, when all of the components are in-service. In the current paper, due to the lack of corrective actions such as BS planning, DRP and vehicle-to-home discharging, etc., the total amount of curtailed load is the same as under naive energy management strategy. The potential of BS, vehicle-to-home and DRP in reducing the overall curtailed load would be investigated in future attempts.

TABLE V
OPERATION COST UNDER NAIVE AND SELF-HEALING ENERGY MANAGEMENT STRATEGY

Case	Naive	Self-healing
Day-ahead	$49.41	$43.26
Real-time (Scen. 1)	$-37.29	$-30.54
Real-time (Scen. 2)	$-35.59	$-25.21
Real-time (Scen. 3)	$-19.86	$-25.65
Real-time (Scen. 4)	$9.46	$9.462
Real-time (Scen. 5)	$-14.53	$-20.32
Real-time (Scen. 6)	$8.40	$14.79
Real-time (Scen. 7)	$43.06	$38.86
Real-time (Scen. 8)	$44.75	$44.19
Expected cost	$28.55	$25.79

V. CONCLUSION

The self-healing smart buildings are concepts for smart nano-grids with a resiliency-oriented design. Although there are numerous works that investigated the resiliency and reliability of energy systems on a grid-scale, only a handful of works studied home-scale problems. Meanwhile, these works missed some important operational aspects, including the failure rate, MTTR of equipment and uncertainties associated with real-time outages. The mentioned gaps are seen in the presented paper by directing a two-stage hybrid robust-stochastic programming. For this purpose, bi-level programming is inspired by the attacker-defender concept to identify the critical faults and based on sequence and continuity of failures of components during daily operation, and generate operational scenarios. Based on these scenarios, and considering the failure rate for each component, two-stage stochastic programming is developed for energy management of the building in day-ahead and real-time markets. The results indicated that the proposed method could be employed for a home-scale application with several components in an efficient simulation time lower than one minute. It should be noted that the computation time will increase by the number of involved components. The simulation results can be summarized as follows. For the studied smart building, the daily operational cost is expected to increase from $ 25.794 (for the deterministic case) to $ 28.097 (for the most conservative case) due to the uncertainty of real-time market prices. Due to power shortages caused by the failure of components, the total expected not-supplied load is 6.72 kW (2.53%). A comparison between a naive, and self-healing scheduling indicated that a naive energy management will charge additional $ 2.75 without considering the probability of components failures under the deterministic case. It is evident that this additional charge is more considerable under robust strategy with the worst realization of real-time prices. It is concluded that the proposed energy management system can anticipate and schedule the resources more efficiently compared with naive strategy but it is still passive to restore curtailed load and it is required to be combined with P2P and SOS schemes to cover more load demands. Moreover, it is expected that predictive optimization concepts, such as the rolling-horizon-based method, can significantly improve the overall efficiency and resiliency when coordinated with the proposed self-healing method. The authors are interested in the mentioned research gaps and tries to fulfill them in probable future attempts.

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