A Two-Stage Optimization Model for Risk-Based Off-Grid Zero-Energy Building Planning

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Zero-energy buildings (ZEBs) have emerged as a promising design approach to address environmental concerns and achieve long-term cost savings for governments and customers. However, geographical and climate situations like being or difficult-to-access locations, as well as regions well-suited for renewable energy, have attracted attention to off-grid ZEBs. These off-grid ZEBs provide an effective solution for customers residing in such regions by harnessing the concept of supplying building demand through a standalone energy system independent of urban electricity infrastructure. Passive design, particularly through the use of envelope thermal insulation, plays a crucial role in enhancing the energy efficiency of buildings. This paper presents a two-stage optimization model of risk-based off-grid ZEB planning in hot climate regions, which encompasses of sizing the standalone energy system and designing the required thermal insulation. At the upper level, the focus is on identifying the most cost-effective capacities for the energy resources and determining the appropriate parameters for insulation design. The lower-level problem, embedded within a scheduling model, extracts the expected annual operation cost in order to ensure the feasibility of the sizing problem and meet the annual electric demand. The robust approach as the risk management tool is employed to mitigate the inherent uncertainty associated with the building demand. Furthermore, the two-stage problem is tackled through a hybrid algorithm, composed of numerical metaheuristic and mathematical programming methods. Moreover, an industrial campus in Kish Island is selected as the simulation case study to validate the proposed approach in creating an off-grid energy-efficient system. The standalone energy system of DG-PV-storage integration results in an 8% reduction in planning cost compared to the only-DG system, with a 9% decrease in DG capacity. Additionally, incorporating insulation design using XPS material leads to a further overall cost reduction of 22%, accompanied by a reduction of 47 m^2 in PV panel area.

keywords: *ZEB, hybrid PSO-MILP, insulating, PV, storage, risk, passive design.*

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NOMENCLATURE

i, Ω^{ins}	Set of insulation types
h	hour
y	Planning year
l	External wall layer index
ρ^{ins}	Insulation price ($\$/m^3$)
CC^{DG}	Capital cost of DG ($/kW)
MC^{DG}	Maintenance cost of DG ($/h)
CC^{PV}	Capital cost of PV ($/kW)
MC^{PV}	Maintenance cost of PV ($\$/m^2$)
CC^{ST}	Capital cost of storage ($/kW)
MC^{ST}	Maintenance cost of storage ($/kWh)
int_r	Interest rate

inf_r Inflation rate
ρ^{DG} Operation price of DG (\$/kWh)
η_{ST} Efficiency of storage
TED Total electric load (kW)
η^{PV} Efficiency of PV
G_h Hourly solar irradiation (kW/m^2)
CDH Cooling degree hour (C)
Γ Budget of uncertainty
R Thermal resistance (m^2.K/W)
T_h Hourly temperature (C)
λ^w Thermal conductivity
WWR Window to wall ratio
A^w Insulating area (m^2)
x^w Insulation thickness (m)
ψ^{DG} DG capacity (kW)
Φ^{PV} PV capacity (kW)
Φ^{ST} Storage capacity (kW)
P^{DG} DG power (kW)
Z^{DG} Binary state variable of DG
u_i Binary variable vector of insulation selection
z^{ch} Charge state of storage
z^{dc} Discharge state of storage
P^{ch} Charge power of storage
P^{dc} Discharge power of storage
C^{ST} Energy capacity of storage
A^{PV} Area of PV array
ΔE Reduced cooling demand
q_h, δh, M Auxiliary decision variables used Robust modeling

1. INTRODUCTION

A. Zero energy buildings

A zero-energy building (ZEB) is a structure that is designed and built to generate as much energy as it consumes over the course of a year. This is achieved through a combination of energy-efficient design strategies, renewable energy sources, and on-site energy generation. The goal of zero-energy buildings is to minimize the reliance on fossil fuel-based energy sources and reduce greenhouse gas emissions. These buildings often incorporate features such as solar panels, high levels of insulation, efficient lighting and appliances, and advanced building automation systems. By optimizing energy use and utilizing renewable energy, zero-energy buildings can significantly reduce energy costs and have a positive environmental impact. Governments have increasingly shown their support for the development of ZEBs due to various reasons associated with energy issues. The combustion of fossil fuels as a means of energy production significantly contributes to the emission of greenhouse gases, which are prime drivers of climate change. ZEBs, on the other hand, operate on renewable energy sources and exhibit high levels of energy efficiency. As a result, they effectively minimize the carbon footprint of buildings, thereby aiding in the mitigation of climate change. Additionally, dependence on imported energy sources can expose countries to fluctuations in prices and geopolitical tensions. By investing in ZEBs and other alternative energy forms, governments can reduce their reliance on fossil fuels, consequently enhancing energy security. Lastly, the escalating costs of energy can impose substantial burdens on both households and businesses, and this is where ZEBs provide considerable relief. By reducing energy consumption, ZEBs can effectively decrease energy bills, making energy more affordable for all parties involved [1–3].

One essential aspect of the concept behind ZEBs revolves around passive design. Passive design entails the utilization of design strategies that maximize natural sources of heating, cooling, and lighting in order to minimize the reliance on mechanical systems and reduce energy consumption. The primary objective of passive design is to create indoor environments that are both comfortable and energy-efficient, ultimately reducing the carbon footprint of the building. Passive design strategies encompass several methods, including optimizing the orientation of the building [4], insulating walls, roofs, and floors [5–7], insulating windows [8], thermal mass such as concrete and brick [9, 10], solar reflecting paints for walls [11–13], daylighting [14, 15] and shading devices, such as awnings and blinds [16–21].

When it comes to meeting the energy demands of ZEBs, it is desirable to rely on clean and carbon-free renewable resources, such as photovoltaic (PV) units. These resources not only contribute to reducing the operation costs but also pose a lower environmental impact compared to fossil fuel-based resources [22]. Hence, efficient sizing of these resources is crucial in creating a cost-effective ZEB, considering the current high investment costs associated with renewable units like PV [23]. The studies on various climatic conditions and their influence on the optimal passive-active design of ZEBs have been addressed in [24]. Additionally, authors of [25] proposed a machine learning-based approach to mitigate the optimal energy management of ZEBs, particularly focusing on renewable generation forecasting. Furthermore, the integration of a multi-pane glazed all-glass PV system and battery storage in ZEB design, taking into account building anatomy, has been investigated by [26].

Authors in [27] investigated a multi-objective optimization design strategy for zero-energy residential buildings, focused on lowering thermal load and investment costs and extracting a higher PV power output. This approach utilizes the parametric design tool offered by the Grasshopper platform, as well as the Non-Dominated Sorting Genetic Algorithm II. Ref. [28] implemented a dynamic simulation through an integrated energy-economic analysis to assess the feasibility of new Net ZEB offices in different Italian climate zones.

Optimal design of zero-energy PV-integrated buildings was addressed by [29, 30], focusing on the climate changes, global horizontal irradiation and meeting demand. The optimal integration of renewable PV and hydrogen energy storage units to power a ZEB was studied by [31, 32]. The transient behavior of such an energy system evaluated the thermal comfort and represented the role of hydrogen storage in hot water provision for the occupants of the building.

Several diverse criteria can inform the planning of the energy system and the design of ZEBs [33]. These criteria include but are not limited to: minimizing costs and energy consumption [34], considering economic and environmental aspects within a fuzzy multi-criteria framework while accounting for uncertainties [35], reducing lifecycle costs and lifecycle energy consumption [36], minimizing the overall cost and energy loss while maximizing thermal comfort [37]. To enhance the energy efficiency, thermal comfort, and visual comfort of a ZEB, it has been explored that optimal retrofitting can be achieved through integrating photovoltaic systems and controlling passive design parameters such as envelope insulation, heating, ventilation and air conditioning (HVAC) systems, shading, and windows [38, 39]. Moreover, authors in [40] proposed a comprehensive framework for retrofitting existing buildings to transform them into ZEBs. The framework outlines step-by-step procedures for successful retrofitting planning, which involve data collection, life cycle cost calculations, building simulations, and multi-criteria decision-making based on the analytic hierarchy process (AHP). The study conducted in [41] focused on achieving a grid-interactive near-ZEB design by employing a multi-objective approach. The researchers utilized the glowworm swarm algorithm to enhance the optimization problem and find the most optimal solution. Ref. [42] assessed the feasibility of a biomass-driven cogeneration system for a grid-connected ZEB, with the objective of meeting the energy demands, including electricity, hot water, cooling, and heating throughout the year. The planning problem was modeled within a multi-objective framework using nondominated sorting genetic algorithm II (NSGA-II).

Ref. [43] investigated the optimal sizing of PV systems to create a ZEB without concerning the impact of passive design tools like insulation. Ref. [44], conducted a risk-based planning of a standalone energy system along with optimal selection of the insulation material to reach a cost-effective ZEB. However, the type of insulation material used for energy-saving enhancement can optimally impact the total cost of ZEB creation [45, 46]. Also, the factors like thermal inertia and comfortability are affected by optimally selecting the insulating material and type [47]. Authors in [48] developed a multi-criteria approach to rank the insulation material and obtain the optimum thickness values used for ZEB planning. Ref. [49] carried out an optimal decision-based passive design of a building by considering the inherent uncertainties and controlling the design parameters and insulation thickness as the main term. Ref. [50] dealt with risks associated with the uncertainties in future costs to address the optimal and cost-efficient design of a ZEB.

B. Contribution

After reviewing previous research on ZEBs, it becomes evident that they can be categorized into various areas of study, including optimal energy system sizing, multi-criteria design, analysis of thermal behavior, impact of climate change on PV generation, optimal retrofitting, and optimal passive design to enhance energy efficiency. Also, recent studies have employed various metaheuristic optimization algorithms to address the design challenges of ZEBs, employing either single or multi-objective approaches. However, these studies lack a comprehensive and cohesive framework that provides a holistic view of standalone energy system design and the influence of insulation design on the sizing problem. Additionally, the sizing problem extends beyond considering investment costs alone. It should be noted that achieving optimal scheduling of the energy system while accommodating the demands of passive cooling necessitates the utilization of a well-defined programming model. Furthermore, they fall short of providing a risk analysis to account for the effects of uncertainty on overall planning. These two aspects complicate the optimization modeling and introduce significant nonlinearity into the ZEB planning problem.

This paper aims to investigate the optimal planning of a standalone energy system for an electrically off-grid ZEB, considering the impact of passive design. The concept of this ZEB is implemented in an industrial campus situated on Kish Island, with the objective of achieving self-sufficiency and isolation from the electric utility grid. The planning of the standalone energy system entails determining the appropriate sizes for the diesel generator (DG), PV, and energy storage units, which are integrated to meet the campus's electricity demand. It is important to note that the presence of the DG enhances the system's reliability, albeit at the expense of fuel operation costs and carbon emissions for the campus owner.

In tropical regions, the cooling demand in buildings constitutes a significant portion of the electricity load. In addition to the standalone energy system, passive design measures can help reduce the cooling demand and interact with the sizing problem. Passive design refers to selecting cost-effective insulation materials, determining their thickness, and calculating the area required on the external walls of the building. The capacity of the energy system must meet the total electrical demand of the ZEB throughout the year. Therefore, employing an optimal thermal insulation design can lead to a significant decrease in cooling demand and reduce the overall capacity requirements.

Furthermore, some parameters exist in this problem, like the electrical demand of the buildings that are inherent to uncertainty and put the long-term planning at risk. To cope with these uncertainties, different methods like Conditional Value-at-Risk (CVaR), Variance, and Shortfall as the scenario-based risk management methods have been introduced [51]. However, a Robust modeling framework is implemented in this paper to mitigate the uncertainty of the annual electrical demand, which regards the worst-case scenario of the electrical demand in the off-grid ZEB planning problem. Notwithstanding the low flexibility compared to stochastic optimization methods like CVaR, Robust optimization imposes a lower computational burden [52].

Due to the complexity of the ZEB planning problem, (as will be discussed later), the authors of this paper propose a hybrid solve approach, which uses particle swarm optimization (PSO) as the metaheuristic optimization method and mixed-integer linear programming (MILP) as the mathematical programming method. This hybrid PSO-MILP approach represents a bi-level optimization model, which offers cost-effective planning solutions for off-grid ZEB creation. At the lower level, the approach utilizes MILP to address the yearly scheduling problem pertaining to the standalone energy system. Meanwhile, the upper level employs the PSO algorithm to optimize the overall planning problem. Additionally, the authors incorporate the Robust approach to enable optimization of the long-term planning problem under different risk strategies employed by decision-makers. The lower level problem is solved using the Robust MILP (RMILP), converting the optimization process into the hybrid PSO-RMILP.

According to the stated contents, the main objectives of this paper are listed below:

- a two-stage optimization approach to model the ZEB planning problem
- optimal sizing of standalone energy system under the effect of optimal insulating design
- a hybrid PSO-RMILP algorithm to solve the ZEB planning problem under risk management

The rest of the paper is structured as follows. Section 2 defines and formulates the problem and gives an explanation of the proposed optimization method. Section 3 evaluates the results by performing the simulation for an isolated building located on Kish Island, and finally, the conclusion is provided in section 4

2. PROPOSED METHODOLOGY

A. Problem formulation

In this paper, optimal long-term planning of off-grid ZEB for an isolated energy system is studied. This problem consists of three parts, the passive planning of the building, sizing of the integrated energy resources, and scheduling of this standalone system to have the least operation cost. This optimal scheduling is performed concerning the saved energy amount and determined DG-PV-storage sizes. The whole planning of the off-grid ZEB is modeled as below with the objective function in (1) and its relevant equations and constraints in (2)-(20).

$$minTPC = \phi^{ins} + \phi^{PV} + \phi^{PV} + \phi^{ST} + \phi^{opr} \tag{1}$$

where

$$\phi^{ins} = \textstyle\sum_{i \in \Omega_{ins}} u_i \rho_i^{ins} x_i^w A^w \tag{2}$$

$$\textstyle\sum_{i \in \Omega_{ins}} u_i = 1 \tag{3}$$

$$\phi^{DG} = CC^{DG}\psi^{DG} + \sum_{y=1}^{N_y}\sum_{h=1}^{N_h} MC^{DG}\psi^{DG} PWF_y \tag{4}$$

$$\phi^{PV} = CC^{PV}\psi^{PV} + \sum_{y=1}^{N_y}\sum_{h=1}^{N_h} MC^{PV}\psi^{PV} PWF_y \tag{5}$$

$$\phi^{ST} = CC^{ST}\psi^{ST} + \sum_{y=1}^{N_y}\sum_{h=1}^{N_h} MC^{ST}\psi^{ST} PWF_y \tag{6}$$

$$\phi^{opr} = \sum_{y=1}^{N_y}\sum_{h=1}^{N_h} \rho^{DG} (a^{DG} P_{h,y}^{DG} + b^{DG}\psi^{PV}) PWF_y \tag{7}$$

$$PWF_y = \left(\tfrac{1+\text{int\_}r}{1+\text{inf\_}r}\right)^y \tag{8}$$

Subject to

$$z_{h,y}^{DG}.P_{\min}{}^{DG} \le P_{h,y}^{DG} \le z_{h,y}^{DG}.P_{\max}{}^{DG} \tag{9}$$

$$z_{h,y}^{ch}.P_{\min}{}^{ST} \le P_{h,y}^{ch} \le z_{h,y}^{ch}.P_{\max}{}^{ST} \tag{10}$$

$$z_{h,y}^{dc}.P_{\min}{}^{ST} \le P_{h,y}^{dc} \le z_{h,y}^{dc}.P_{\max}{}^{ST} \tag{11}$$

$$C_{h,y}^{ST} = C_{h-1,y}^{ST} + \eta^{ST} P_{h,y}^{ch} - P_{h,y}^{dc}/\eta^{ST} \tag{12}$$

$$z_{h,y}^{ch} + z_{h,y}^{dc} \le 1 \tag{13}$$

$$P_{\max}{}^{ST} = \alpha_{\max}\psi^{ST}, P_{\min}{}^{ST} = \alpha_{\min}\psi^{ST} \tag{14}$$

$$P_{h,y}^{DG} + P_{h,y}^{PV} + P_{h,y}^{dc} \ge P_{h,y}^{ch} + T\hat{E}D_{(h,y)} - \Delta E_{h,y} \tag{15}$$

$$P_h^{PV} = A^{PV}\eta^{PV}\eta^{Con} G_h \tag{16}$$

$$\Delta E_h = 0.001 \times CDH_h \times (ETTV_h^0 - ETTV_h^1) \times A^w/COP \tag{17}$$

$$CDH_h = \begin{cases} T_h - T_b & T_h > T_{ref} \\ 0 & T_h > T_{ref} \end{cases} \tag{18}$$

$$\begin{aligned} ETTV_h^0 = (1 - WWR) \times U_w^0 + WWR \times U_f \\ WWR \times SF \times SC \times CF \end{aligned} \tag{19}$$

$$\begin{aligned} ETTV_h^1 = (1 - WWR) \times U_w^1 + WWR \times U_f \\ WWR \times SF \times SC \times CF \end{aligned} \tag{20}$$

$$U_w^0 = \frac{1}{\sum_{l=1}^{N_l} R_l} \tag{21}$$

$$U_w^0 = \frac{1}{\sum_{l=1}^{N_l} R_l + \frac{x^w}{\lambda^w}} \tag{22}$$

The objective function in (1), calculates the total planning cost (TPC) that is quantified into five terms, insulation cost ϕ^{ins}, DG (capital and maintenance) cost ϕ^{DG}, PV cost ϕ^{PV}, storage cost ϕ^{ST}, and DG operation cost ϕ^{opr}. The cost pertaining to insulating external walls is defined in (2) and depends on the insulation material type selected from the given set Ω^{ins}, insulation thickness, and the maximum insulation surface implemented in the building. u is a binary decision variable vector that is 1 if the insulation material type i is selected. According to (3), just one insulation type can be selected. The costs pertaining to the sizing of DG, PV, and storage units in (4)-(6) include the capital investment cost and the maintenance cost based on their selected size. Equation (7). represents the operation cost of the DG through the lifetime horizon. The parameters a^DG and b^DG are the fuel consumption coefficients with values of a^DG=0.246 L/kWh and b^DG=0.08145 L/kWh [53]. Also, the parameter PWF denotes the present worth factor (8). DG output power is bounded by inequality (9). Binary variable $z_{h,y}^{DG}$ determines the on/off states of the DG unit. Inequalities (10) and (11), stand for the limitation in the charge and discharge power of the storage system. As well as (9), two binary decision variables $z_{h,y}^{ch}$ and $z_{h,y}^{dc}$ define the charge and discharge states of the storage. Capacity update of the storage is formulated in (12). Constraint (13) indicates that the storage can take one of the charge, discharge, or idle states in each hour. Minimum and maximum charge/discharge power rates of the storage are determined based on the specific percentages of the selected storage size α_{min} and α_{max} as (14). Constraint (15) states that the generation capacity of the building should be as enough as the hourly generation is greater than the hourly demand. $T\hat{E}D$ is the forecasted total hourly electrical demand. PV output power is calculated by (16) and depends on its total area, PV efficiency, converter efficiency η^{Con} and solar irradiation. Variable ΔE stands for the reduced amount in the hourly cooling load of the building and is defined as (17) and is calculated by the envelope thermal transfer value (ETTV) index [54]. This index expresses the kW amount of thermal load imposed on the building by heat transfer from the ambient to the building indoors through each square meter of the envelopes. The superscripts 0 and 1 respectively denote the external walls without insulation and with insulation. CDH as the cooling degree hour equals 0 for the ambient temperatures less than the reference temperature and equals their difference for other cases (18). The ETTV index is defined for two cases of uninsulated and insulated as (19) and (20), in which U_w and U_f are thermal transmittance values of walls and fenestration (W/m^2), WWR is the window-to-wall ratio of the building, SF is the solar factor, CF is the solar correction factor and SC is the shading coefficient of fenestration. The thermal transmittance of walls for the two aforementioned cases and depending on the external wall layers is calculated by (21) and (22). R is the thermal resistance of the materials in the walls that is equivalent to the ratio of material depth to its thermal conductivity λ (and this is valid for the utilized insulation material).

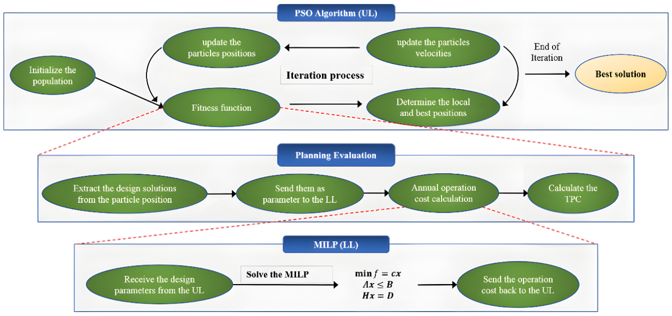

Fig. 1. Steps of the PSO-MILP algorithm

B. PSO-MILP algorithm

The abovementioned problem formulation is a mixed-integer nonlinear programming model with a relatively high degree of nonlinearity. To simplify the problem, the annual consumption of the building, annual solar irradiation, and the annual ambient temperature are assumed as the forecasted amounts for all the planning years. As this is a large-size problem and hard to solve because of its high nonlinearity, the authors propose to split the problem into a bi-level form (23). The upper level (UL) determines insulation material type, its thickness and maximum area, PV size, and energy storage size concerning the operation cost calculated in the lower level (LL) problem. The LL problem is a MILP model considering the UL variables as parameters. It should be noted that since this problem is carried out for an area with almost unchanged annual electric demand, it is assumed that the scheduling of the off-grid ZEB for one year serves the goal.

$$UL:\begin{cases} Min\ \ TPC(u,x^w,A^w,\psi^{PV},\psi^{ST},\psi^{opr}) \\ \qquad s.t.(15)-(21) \\ LL:\begin{cases} Min\ \ \phi^{opr} \\ s.t.(8)-(14) \end{cases} \end{cases} \tag{23}$$

To solve this problem, a hybrid PSO-MILP method is proposed. PSO accounted as the family member of metaheuristic evolutionary algorithms is appropriate to numerically solve complicated nonlinear optimization problems [55]. The basis of PSO is inspired by the birds' motion and reaches the optimal solution by randomly generation of primary solution population and updating them in each iteration as (24). In these two equations, X_i^t and V_i^t are the$i'th$generated solution vector (particle position) and their respective velocity vector in iteration $t.p^{best}$ and g^{best} respectively denote the best and global solutions and ω, c_1, c_2, r_1^t, r_2^t are the PSO parameters.

$$\begin{aligned} V_i^{t+1} &= \omega V_i^t + c_1 r_1^t (p^{best} - X_i^t) + c_2 r_2^t (g^{best} - X_i^t) \\ X_i^{t+1} &= X_i^t + V_i^{t+1} \end{aligned} \tag{24}$$

Considering X=[u,x^ω,A^ω,ψ^{PV},ψ^{ST}] as the particle position structure, PSO in the UL generates the random solutions and iteratively updates them to reach the global best position. For each solution generated in the UL, the LL problem with the MILP model is solved by taking these solutions as its input parameters. The output of the LL is the annual operation cost of the building that is used in the calculation of the TPC mentioned before. This method dramatically reduces the running time of the simulation. Fig. 1, depicts the whole process of the hybrid PSO-MILP algorithm used to solve the off-grid ZEB planning problem.

C. Robust optimization

Since the proposed off-grid ZEB planning is long-term, considering the uncertainties and their impact on the TPC seems to be of importance. To avoid further complications, the uncertainty is taken into consideration for the annual total electrical demand and ignored for other parameters like solar insolation and temperature. This implies a proper risk-based optimization model to manage the risks and deal with the demand uncertainty as the most influential factor in the off-grid ZEB planning. Also, the LL annual scheduling is a large problem on an hourly basis that can make implementing stochastic optimization methods so difficult. To this end, Robust optimization [56] as a non-probabilistic method is used in this paper to concern the worst-case scenario of the total electrical demand in the planning problem. Unlike the probabilistic methods that are on the basis of the probability distribution functions, the uncertain parameter in Robust optimization is modeled by an interval set as an unknown variable limited within a specific bound. This is shown for hourly total electrical demand in (25) that $T\hat{E}D$states the actual demand, $T\hat{E}D_h$ denotes the forecasted demand and D_h^{min},D_h^{max} indicate the boundaries of the demand.

$$T\hat{E}D_h \in S(TED_h) = \{D_h^{\min} \leq TED_h \leq D_h^{\max}\} \tag{25}$$

After decomposing the primary planning problem into a bi-level problem, it is possible to apply the Robust optimization approach to the LL scheduling problem. By considering the annual generation-demand inequality in (15) and its reformulation as (26)-(28) below, the deterministic LL problem is converted to a Robust MILP (RMILP) with the help of strong duality. Thus, the main off-grid ZEB planning problem is solved through the hybrid PSO-RMILP method.

$$P_h^{DG} + P_h^{PV} + P_h^{dc} \geq P_h^{ch} + (TED_h + M.\Gamma + q_h) - \Delta E_h \tag{26}$$

$$M + q_h \geq (D_h^{\max} - D_h^{\min}).\delta_h \tag{27}$$

$$M \geq 0, \quad q_h \geq 0, \quad \delta_h \geq 1 \tag{28}$$

In these new constraints, Γ is the Robust controlling parameter known as the budget of uncertainty. This parameter here is defined between [0,1] and sets the risk strategy of the planner. The value of 0 gives the previous deterministic model, while the value of $\Gamma = 1$ stands for the highest conservatism or risk-averse strategy of the planner. Also, the continuous decision variables M, q_h, δ_h are deduced from the implementation of the strong duality concept.

3. RESULTS AND DISCUSSIONS

The proposed approach is examined on an existing industrial campus in Kish Island [44], shown in Fig. 2, which includes two office buildings and two industrial buildings. The main goal of the decision-maker is to upgrade these buildings within the off-grid industrial campus to electrically self-sufficient off-grid ZEBs. It is assumed that the buildings' rooftops are insulated before, and the external walls are the candidate locations. Also, all the external walls are assumed to have the same structure as depicted in Fig. 3. They are constructed of three layers of inner

Fig. 2. Industrial campus in Kish Island

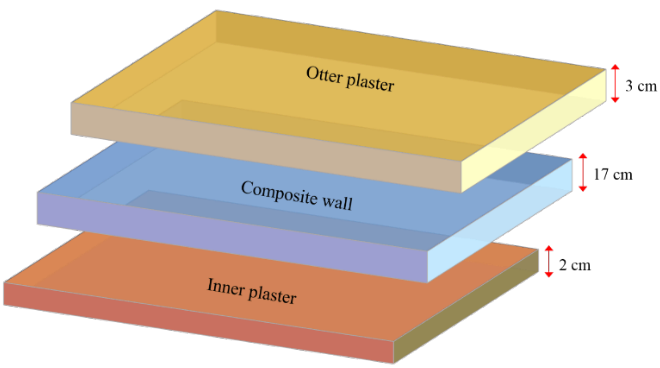

Fig. 3. Wall structure of the buildings within the campus

plaster, composite wall, and otter plaster with depths amounts shown in the figure and thermal conductivity values of 0.87, 0.45, and 1.4 W/mK respectively. The daily total solar insolation and maximum temperature in Kish Island for the period between 20/03/2019 and 19/03/2020 are both respectively represented in Fig. 4 and Fig. 5. Although the related temperature data is given in a daily manner, each value can be assumed as the same for 24 hours of the day to calculate the CDH. These two data are available and accessible in [57]. Also, the total electrical demand, including the cooling demand, is recorded by TDL104 as a data logger device. Fig. 6 shows the pure annual electrical demand of the campus within the same period in the time step of 1 hour. The inflation and interest rates are respectively 8% and 12% too. The reference temperature to calculate the CDH is assumed to be 26o C. The shading coefficient, solar factor, and solar correction factor are 0.4, 210.92, and 1, respectively. Also, the COP value is equal to 3.5. Each office building has a floor area of 300 m^2 with a height of 3 m, while the two industrial buildings have the same area of 800 m^2 and a height of 7 m. The WWR parameter for the office buildings is 0.068 and for the industrial buildings is 0.089. Table 1 gives the required data about the distributed energy resources that can be installed and utilized on the campus. It is assumed that the minimum and maximum storage power rates are 5% and 30% of the selected capacity, respectively. Also, the

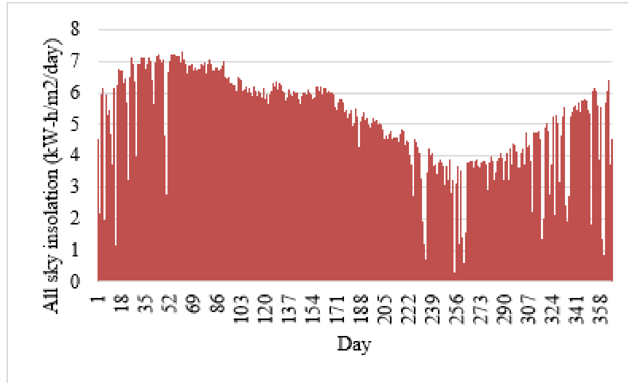

Fig. 4. Daily total insolation in Kish island

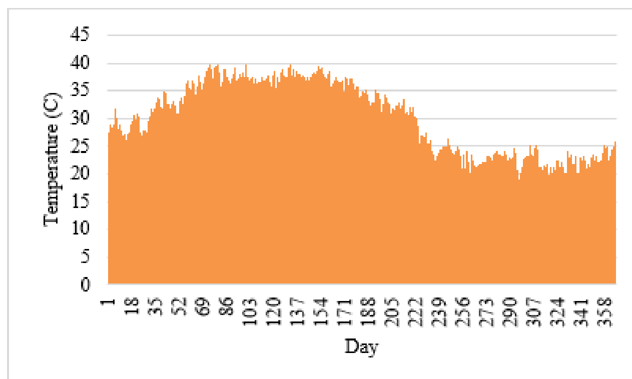

Fig. 5. Daily temperature of Kish Island for one year

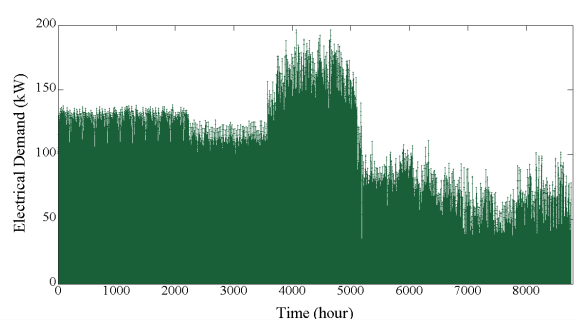

Fig. 6. Hourly total electrical demand through one year

Table 1. Required data for distributed energy resources

Parameter	Value	Parameter	Value
DG capital cost ($/kW)	1521	PV maintenance cost ($/m2)	5.2
DG fuel cost ($/L)	1.2	PV efficiency	0.20
DG maintenance cost ($/h)	0.05	Storage capital cost ($/kW)	200
PV array capital cost ($/m2)	519.7	storage maintenance cost ($/kW)	300

Table 2. Required insulation data

Insulation type	Thermal conductivity (W/mK)	Cost ($/$m^3$)
Expanded polystyrene (EPS)	0.036	188.42
Extruded polystyrene (XPS)	0.029	304.23
Foamed polyvinyl chloride (PVC)	0.024	400

available insulation types to be used in this problem with their relevant thermal conductivity and cost are listed in Table 2. As discussed in the previous section, the problem is solved in the bi-level framework, the upper level is optimized through the PSO in MATLAB software, and the lower level optimization solution is achieved using the CPLEX solver in GAMS. Also, the PSO algorithm is solved by an initial population of 70 and a maximum iteration of 100. The problem is solved for four case studies as below, which make a comparison and verify the validity of the introduced method.

A. DG-based planning of the off-grid ZEBs

In this case study, it is aimed by the decision-maker to supply the electrical demand of the campus by just installing a DG unit. Optimal sizing of the DG for the planning horizon of 20 years (equivalent to the building lifecycle) and concerning the required demand results in a cost of $7.56 million. This cost contains the investment cost of buying and installing the DG and its annual operation and maintenance costs. The optimal size of the DG is 196 kW which is almost equal to the maximum amount of the total electrical demand in the industrial campus. This type of planning enhances the operation cost and greenhouse gas emission (as an environmental issue), despite its highly reliable energy provision with an appropriate capacity selection.

B. DG/PV/storage-based planning of the off-grid ZEBs

This case study lets the decision-maker assess the off-grid ZEBs planning by optimally sizing the DG/PV/storage units. Table 3 shows the results pertaining to the selected capacity of the three energy resources. As it is clear, the chosen capacity of the DG

Table 3. Optimal capacity of the distributed energy resources for case study 2

DG capacity	PV array area	PV capacity	Storage capacity
178 kW	887 m^2	117 kW	60 kWh

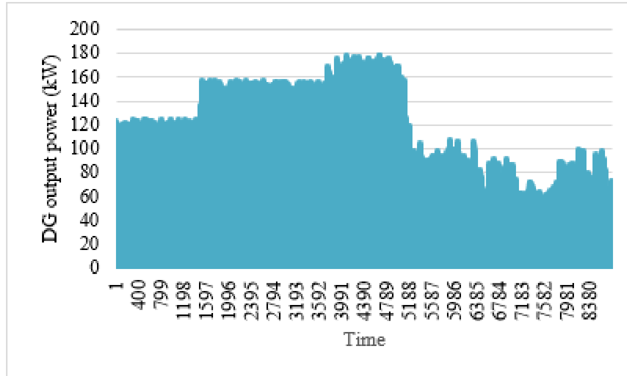

Fig. 7. Scheduled DG output power during one year for case study 2

has a lower value than the one obtained in the previous case study, and this directly refers to the high operation cost incurred by the DG throughout the planning period. Thus, the shortage of generation capacity by lowering the DG size is compensated by locating the PV-storage system with adequate capacity at the site of the campus The TPC of $6.93 million is obtained for this case study, which is composed of a total investment cost equal to 744770 $ and operation and maintenance costs of $6.19 million. Fig. 7 represents the annual DG output power that is expected to be scheduled in 8760 hours of a year. Fig. 7 shows the scheduled power of the storage in which the positive values denote the charge state and the negative values denote the discharge state. As it is seen, the major part of the campus electrical demand is provided by the DG. The PV-storage system supplies the remaining part of the demand, but there is an important point that should be noted.

Fig. 9 shows the output power of the PV system along with the charge/discharge power of the energy storage for hours between 3800-3850. It can be realized from this figure that the PV's highest output power coincides with the charge hours of the storage, which means that the PV output power charges

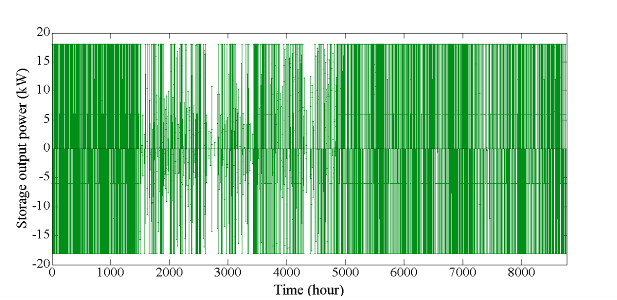

Fig. 8. Scheduled storage output power during one year for case study 2

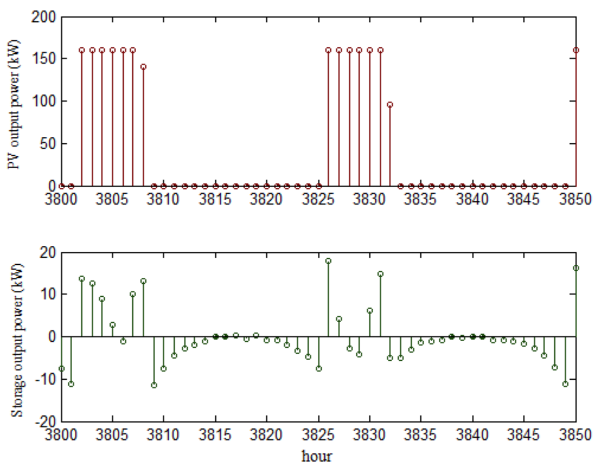

Fig. 9. PV/storage output powers for hours between 3800-3850

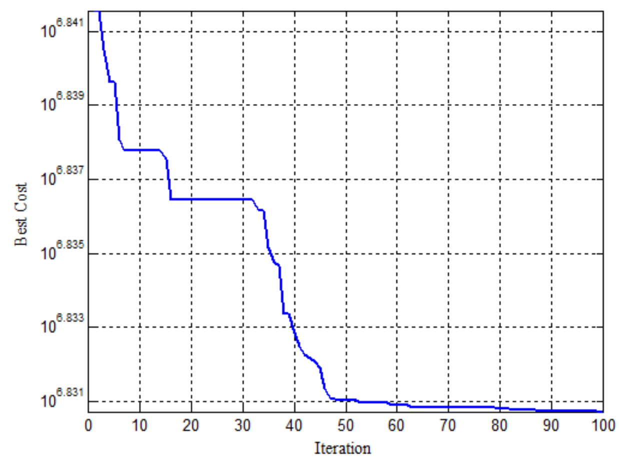

Fig. 10. TPC convergence through the iterative process of the PSO

Table 4. Results pertained to the insulating of the buildings

Building	Insulation material type	Insulation thickness (cm)	Insulating surface (m^2)
Office	XPS	17.81	274
Industrial	XPS	7.53	1020

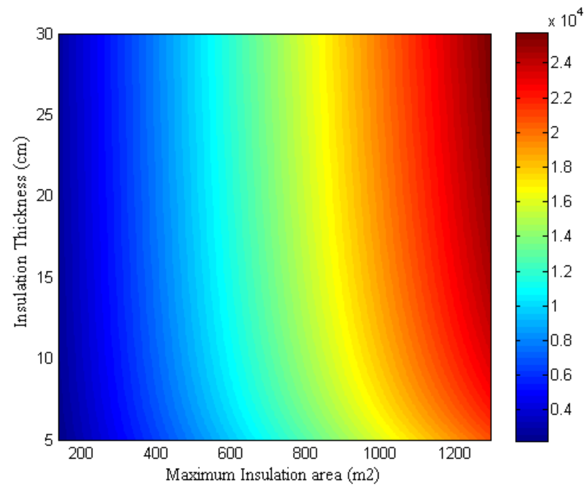

Fig. 11. Annual cooling load reduction in kW versus insulation surface and thickness

the storage. On the other hand, the DG capacity is inadequate relative to the demand in some hours of the year, which implies the installation of a PV with a considerable area along with high-power storage to fill this gap.

C. DG/PV/storage planning beside the buildings passive design

In this case study, the DG/PV/storage planning is evaluated beside the optimal insulation of the four buildings. This insulation as the passive design of the buildings is performed in the first year of the planning and lets the campus owner utilize two types of insulation material at the most for the office and industrial buildings. The initial population number of 70 and iteration number of 100 are applied for this case study, and Fig. 10 shows the convergence process of the total planning cost through the PSO algorithm. Table 4 represents the insulating results on the external walls of the four buildings, including the selected material type, thickness, and maximum insulating surface for each type. The material type, XPS, with the lowest price, is selected to insulate the external walls of the office and industrial buildings. However, their optimum thickness values are different, and thicker insulation is implemented for the office buildings. In addition, the insulation surfaces for the office and industrial buildings are respectively 274 and 1020 m2, equivalent to the external wall areas of these buildings, excluding their window areas. There is an essential point that the insulating cost is directly related to the multiplication of the insulation surface and thickness. However, the priority and prominence of the insulation surface in the obtained optimal solution are evident. In other words, the algorithm tries first to maximize the insulation surface and then selects the optimum thickness to lessen the total planning cost. Its reason can be found in Fig. 11, where the total insulating-dependence annual cooling load reduction is represented versus the insulation surface and thickness. It is seen that in higher insulation surfaces, the amount of reduced cooling load is increased, and also it is clear that the reduction of cooling load by insulation is less independent of the thickness rather than the surface. On the other hand, insulating the external walls just incurs the capital cost. It does not include the operation and maintenance cost, unlike the distributed energy resources with a higher investment cost and substantial operation and maintenance cost for a long-term period. This results in installing thicker insulation on the external wall of the office building with a lower insulating surface and the insulation with a thickness of about 8 cm is utilized for the industrial buildings. The optimal sizes of the distributed energy resources are given in Table 5. By comparing the obtained results in the previous case study, it can be observed that apart from the energy storage, the DG capacity and PV area are reduced. This stands for utilizing the insulation that reduces the total electrical demand and consequently lowers the size of installed energy resource capacity. The obtained TPC in this case study is $5.38 million,

Table 5. Optimal capacity of the distributed energy resources for case study 3

DG capacity	PV array area	PV capacity	Storage capacity
172 kW	840 m^2	168 kW	60 kWh

Table 6. Results pertained to the insulating of the buildings for risk-averse strategy

Building	Insulation material type	Insulation thickness (cm)	Insulating surface (m2)
Office	XPS	11.93	274
Industrial	XPS	11.73	1020

and the cost-saving amount compared to the case without passive cooling is equal to \$1.55 million. This amount belongs to cost-saving over the planning period of 20 years.

D. Robust off-grid ZEB planning

In previous case studies, the budget of uncertainty was 0 to solve the problem deterministically. The last subsection evaluates the risk-based off-grid ZEB planning by applying the Robust optimization approach. As well as subsection 3, the DG/PV/Storage system is intended to supply the electrical demand of the industrial campus actively, and the external wall insulating is aimed at passive cooling of the buildings. By implementing the PSO-RMILP method and setting the uncertainty budget on its maximum amount (Γ=1), the acquired planning results are given in Tables 6 and 7. Note that the total electrical demand is assumed to be bounded within 96% and 105% of its forecasted amount just for simplicity. As the decision-maker adopts the highest conservatism, it is observed that the insulation thickness is increased for industrial buildings with a larger area by about 4 cm. However, the thickness value for the office buildings is reduced compared to the deterministic model, which can be justified since the insulation cost is reduced for office buildings with much lower insulating surfaces. In addition, the optimal DG size and PV area faced a considerable increase by taking the risk-averse strategy, and these all led to the TPC of \$5.91 million. Compared with the obtained result in the deterministic-based off-grid ZEB planning, the TPC is increased by \$523060 belonging to incurred costs over the 20 years. Also, Fig. 12 represents the TPC variation for a different budget of uncertainty values of 0, 0.3, 0.5, 0.8, 1. The increasing pattern is evident in this figure, as the uncertainty budget is increased from 0 to 1, which verifies the validity of the applied PSO-RMILP method.

In the end, Table 8 gives a general comparison between the discussed case studies. Looking at this table, the first case study

Table 7. Optimal capacity of the distributed energy resources for risk-averse strategy

DG capacity	PV array area	PV capacity	Storage capacity
190 kW	892 m^2	178 kW	60 kWh

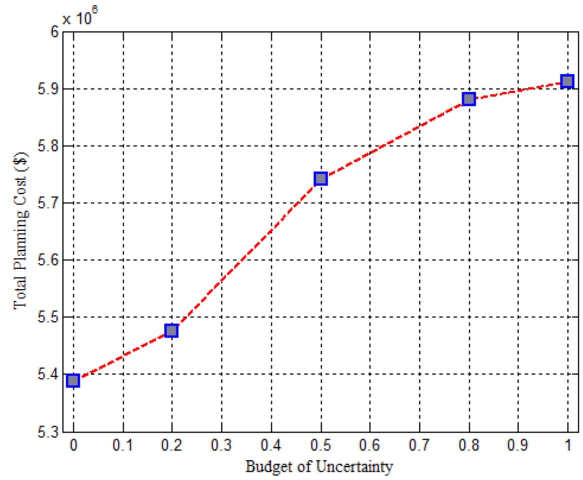

Fig. 12. TPC variations for different values of budget of uncertainty

Table 8. Optimal capacity of the distributed energy resources for risk-averse strategy

Case study	DG size (kW)	PV array area (m2)	Insulation thickness (cm) office	Insulation thickness (cm) Indus	Reduction in cooling demand	TPC (m\$)
#1	196	-	-	-	-	7.56
#2	178	887	-	-	-	6.93
#3	172	840	17.81	7.53	22293	5.38
#4	190	892	11.93	11.73	23857	5.91

imposes the largest DG size and TPC for the assumed lifecycle. The second case improves the TPC by adding the PV-storage system to supply a part of the electrical demand. In case #3, implementing the passive design and installing the insulation on the external walls of the buildings results in lowering the annual cooling demand of the campus and consequently reducing DG/PV sizes. Thus, the TPC is considerably decreased relative to the other cases. By applying the Robust approach and considering the conservatism in the off-grid ZEB planning, the TPC and the capacity of energy resources are raised to meet the load error.

4. CONCLUSIONS

The shift towards ZEBs represents a significant acknowledgment by stakeholders of the urgent need to transition towards a more sustainable and resilient energy system. This system must possess the capacity to effectively tackle the ongoing and complex energy challenges that societies currently confront. Such challenges include the need to reduce carbon emissions, enhance energy security, and improve energy affordability and access. The adoption of ZEBs is an important step in this direction, as it represents a holistic approach to building design and operation that maximizes energy efficiency, minimizes energy waste, and generates or procures renewable energy to meet energy demands. One special kind of ZEB is the off-grid buildings that are operated independently of utility power infrastructure. This paper proposed cost-effective and off-grid ZEB planning for an industrial campus at Kish Island. It is worth noting that the proposed approach is more applicable to the self-sufficiency of existing buildings in tropical regions with relatively low fluctuations in temperature and is not suitable for regions with considerable seasonal climate changes. The proposed planning demonstrates the intrinsic relationship between the optimal sizing of the standalone energy system and the optimal passive design, thereby facilitating the creation of a truly ZEB. Lowering the thermal demand through the external walls' insulation can mutually affect the sizing problem and reduce the investment cost. Thus, a two-stage optimization model with a hybrid PSO-MILP algorithm was proposed to mitigate the nonlinearities and ensure the adequacy of the energy system throughout the year. The key aim of this planning was to determine the insulation material types installed on the external walls, calculation of their optimum thickness and surface such that

- the TPC is reduced in comparison with the planning without utilizing the insulation
- the installed energy resource capacity is enough to supply the total electrical demand

Also, the PSO-RMILP algorithm was proposed in this paper to deal with the high non-linearity of the primary problem and manage the inherent risk by applying the Robust optimization approach. It was observed that in the deterministic model (Γ=0), the selected sizes for both the DG and PV were decreased, and this refers to the passive reduction of the cooling demand by external wall insulating. However, adopting the risk-averse strategy (Γ=1) increased the installed DG size, PV array area, and insulation thickness. Although this conservatism caused the increase in the TPC, the whole capacity of the energy resources is determined to meet the unexpected demand errors during the planning period. The design of ZEBs extends beyond incorporating an independent energy system and can encompass various energy sources such as plug-in electric vehicle parking, hydrogen storage systems, and combined heat and power (CHP) units. This aspect introduces the concept of designing multiple energy carrier systems to achieve ZEB status. The optimal design of these energy systems, which enables power-to-x (P2X) flexibility, directly influences insulation design. This correlation between heat production units and insulation design reduces heat load with lower risk. Furthermore, ZEBs require fewer urban infrastructure resources to meet the demand for alternative energy carriers. A standalone energy system with appropriate design and capacity can result in reduced utility bills (including gas and water) throughout the year. However, it should be noted that the initial purchase and installation costs of energy sources, variable weather conditions, and annual increases in electricity prices pose limitations to conducting research on this subject.

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