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with an energy management system**

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Abstract: This paper proposes a bilevel formulation for a coupled planning and operation problem of an advanced microgrid. The proposed model, recast as a mathematical program with equilibrium constraints (MPEC), determines jointly the optimal configuration of the microgrid, while optimizing the output of the distributed energy resources (DER) through the implementation of an energy management system (EMS). The approach further analyzes the available investment options for the microgrid using capital budgeting techniques to determine the return on investment to various microgrid stakeholders. The proposed approach was applied to the energy infrastructure of an off-grid mine. Results obtained through its application show significant savings in the cost of energy and improved benefits to stakeholders.

Key Words: Economic analysis, energy management, distributed energy resources, microgrids, optimization, power system planning.

Résumé :   Cet article propose une formulation par optimisation bi-niveau pour effectuer la conception d'un micro-réseau alimentant un complexe industriel autonome sur le point de vue énergétique. L'approche proposée consiste en un jeu de type Stackelberg où le concepteur, au niveau supérieur, pose la configuration du micro-réseau et où, au niveau inférieur, un système de gestion de l'énergie tente de minimiser les coûts d'exploitation des installations en fonction de la conception proposée. Le modèle est transformé en un problème de programmation mathématique sous contrainte d'équilibre. Le résultat final est une conception optimale de l'infrastructure du micro-réseau. Celle-ci forme le meilleur compromis entre les coûts d'investissement et les coûts d'exploitation du micro-réseau tout au long de sa vie utile. On y présente une étude de cas approfondie où l'on examine l'applicabilité de l'approche pour la mise à niveau de l'infrastructure énergétique d'une mine autonome située dans le nord du Québec. On démontre également comment l'approche proposée ici permet d'améliorer le rendement économique de la conception en comparaison à la conception déterminée par un outil informatique commercial voué à la conception optimale des micro-réseaux.

Nomenclature

The main symbols used in the paper are listed here for the convenience of the reader.

A. Indices

i Index for all energy resources

t Index for time

h Superscript for heat/thermal resources

e Superscript for electrical resources

y Index for years of project lifetime

r Index of demand response (DR)

B. Sets

E Set of indices of electrical output of resource i

H Set of indices of thermal output of resource i

B Set of indices of all new DERs

$\bar{B}$ Set of indices of new DERs except storage

A Set of existing resources i in the network

G Set of dispatchable generating units

D Set of indices of diesel generating units

N Set of indices of combined heat and power (CHP) units

Q Set of indices of non-CHP gas fired thermal units

S Set of indices of storage devices

W Set of indices of wind power generating units

Y Set of indices of years y in the project lifetime J

T Set of indices of time t within a year

C. Parameters

v_i Energy to capacity ratio of storage resource i

k_r^e Electrical DR energy to power ratio

k_r^h Thermal DR energy to power ratio

w_r^e Percentage of electrical load available for DR

w_r^h Percentage of thermal load available for DR

C_i^b Budget constraint for resource i

C_i^c Capital expenditure of resource i

C_i^f Fuel cost for resource i

C_i^z Emissions cost for resource i

C_i^m Maintenance cost for resource i

$X_i^{\max}$ Maximum power capacity of for a new resource i

$P_i^{\max}$ Maximum power output of existing resource i

$P_i^{\min}$ Minimum power output of existing resource i

$L^e(t)$ Electrical load at time t

$L^h(t)$ Thermal load at time t

$L^{e,\max}$ Peak electrical load

$L^{h,\max}$ Peak thermal load

a_i Power capacity of existing asset i

η Storage charging and discharging efficiency

ς Electric to heat ratio of CHP unit

D. Operation level variables

$P_i^e(t)$ Hourly electrical output of resource i

$P_i^h(t)$ Hourly thermal output of resource i

$P_r^e(t)$ Hourly electric power from demand response

$P_r^h(t)$ Hourly thermal output from demand response

$E_i^e(t)$ Electrical energy level of resource i at time t

E. Design level variables

x_i Capacity of DER assets to be installed

1 Introduction

With an increased focus on reliability and a desire to reduce its environmental impacts, power system planners are exploring the advantages of distributed energy resources to compliment central grid infrastructures. Government policies, technological advancement, economic and environmental incentives are changing the features of power systems, while distributed energy resources (DERs) gradually increase their presence. Many key industrial players have developed energy saving strategies and are investing in renewable energy infrastructure.

In the same vein, microgrids can be seen as vehicles for a greater integration of renewable energy resources (RES), the reduction in emissions of greenhouse gases, improving local system reliability and efficiency, as well as to manage and control power generation. It is defined as a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid [1]. Nevertheless, the microgrid concept and functionalities have evolved over the years from providing emergency energy supply for reliability to include an energy management system that should optimally allocate energy resources to minimize cost. The concept and its changing functionalities characterizing advanced microgrids are described in details in [2]. It is clear that the successful implementation of advanced microgrids will require advance planning strategies seeking to best balance operational and financial benefits.

Most research work reported in the technical literature on microgrid planning and operation appears to decouple the investment planning problem from the microgrid operational problem. Authors in [3], [4] proposed a planning formulation that seeks to determine the sizing and configuration of microgrids. Specifically, the proposed approach in [3] utilizes a mixed-integer linear programming (MILP) formulation and solution algorithm to determine the configuration of a potential microgrid that minimizes its energy procurement cost and CO_2 emissions. This was further extended in developing the DERCAM software package [4]. In [5]–[7], evolutionary algorithms are outlined to solve a decoupled planning problem; they also attempt to determine the optimal location of DERs within a microgrid. A benefit to cost ratio is also implored in [6] for determining the best planning option. With regards to operational planning, the authors in [7], [8] proposed dispatch strategies to optimize the operational cost of remote microgrids. Likewise, a computer-aided demand management system (CADMS) for a large-scale gold mining operation is developed in [9]. The objective of a CADMS is to provide a responsive computational aid and adaptive control system for effective demand management. Miller et al. also suggested features that would enable advanced energy management practice for mineral extracting operations [10].

Clearly, if one is attempting to choose and size the components of a microgrid, there is a need to have a reflection of the expected operations into the design problem. At the same time, it is clear that past microgrid design decisions can have a direct incidence upon the operating costs and space. Therefore, there is a need to find a way to unify these two with the objective of finding the *best microgrid design* which would provide

the *best operating costs* over the microgrid's assets lifetime. The idea here could be seen as a repeated game where the microgrid designer "plays" a microgrid configuration with the objective of maximizing its own payoff (the net present value of the microgrid) to the microgrid operator. Given the move of the designer, the operator would also "play" to maximize its payoff by minimizing the microgrid running costs. The designer, observing the operator's actions, could then play a new design which the operator would then play on. This process could go on until the designer and operator find an equilibrium (fixed point) of the game where neither of them has an incentive to change their play, *i.e.*, the microgrid design and the operating strategy.

The above description, which corresponds to a classic Stackelberg leader-follower game, can be cast as a bilevel optimization problem [11]. Detailed background on bilevel optimization can be found in [11]–[13]. Among examples of bilevel optimization in power systems, we find [14] where its authors have developed a two-step MILP model that optimizes the configuration of a hybrid microgrid design and determines the optimal hourly dispatch. The first step solves an MILP model of the hybrid design, the solution is then passed to the second step which performs a data mining analysis to determine the best controller strategy. A bilevel model of a microgrid planing based on Benders' decomposition with uncertain physical and financial information is also proposed in [15]. The authors of [16] also attempt to nest the microgrid planning and operational problem in the form of a generalized double-shell framework based on an evolutionary algorithm. However, the economic analysis of the design options in [16] was not fully exploited. Morris et al. developed a framework for quantifying the benefits of microgrids and their interrelationships based on the Unified Modeling Language (UML) use case paradigm considering the participation of various stakeholders [17]. A methodology is further outlined in [18] to optimize the microgrid benefits identified in [17] from a planning perspective.

It is evident from the above review that research work on microgrid planning is limited with most of the existing approaches decoupling the planning and operational problems. The aim of this paper is to develop an effective microgrid bilevel planning approach that couples both problems into a single formulation, alike the leader-follower game described before. The model involves a two way interaction between the designer and an energy management system (EMS) which acts as a proxy system operator. The approaches in [17] and [18] are further exploited in this work to provide an economic justification for different investment options. To this end, the main contributions of this paper are:

1. We develop a systematic bilevel optimization problem capable of combine microgrid planning and operation.
2. A reformulation of this problem as mathematical problem with equilibrium constraints (MPEC) via the strong duality theorem and its further transformation into an equivalent MILP problem.
3. A demonstration of its practicality in designing the energy infrastructure of a remote mining operation.

The rest of the paper is structured as follows: Section 2 outlines the proposed bilevel formulation and its transformation into an MILP problem. Section 3 provides an economic analysis of the planning options. Section 4 then describes an application of the proposed formulation to a representative off-grid mining operation, and Section 5 discusses the results obtained. Section 6 finally provides brief concluding remarks.

2   Problem formulation

2.1   Bilevel model outline

As previously mentioned, the coupled planning and operational problem can be formulated as a bilevel optimization problem, as illustrated in Figure 1. Herein the microgrid designer, acting as the leader, is represented by the upper level problem while the lower level represents the EMS (operator proxy) which acts as the follower. The designer receives input information about the planning horizon, peak load, available DER options with their possible ratings and economic parameters (*i.e.*, capital costs of DERs, interest rate, budget constraints and other capital expenses). It then selects a design configuration (capacity of DERs, x_i $i \in B$, where B is the set of all DER options) seeking to maximize its payoff and passes it to the EMS. The capacities from the upper level serve as parameters in the lower level problem defining the inducible
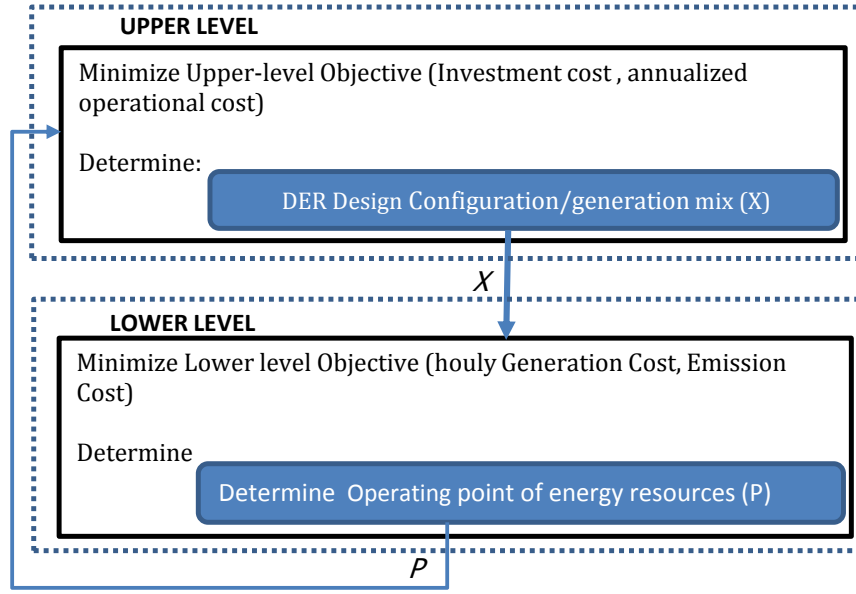
Figure 1: Schematic diagram of the bilevel design-operating model.

region of the lower level problem. The EMS thus determines the operating points of the DERs minimizing its hourly running costs based on the parameters received. The hourly running costs and DER set points (P_i) are passed back to the upper level to evaluate the total cost over the entire planning horizon. The designer, observing the EMS' selection, optimizes its objective and passes a new configuration to the lower level problem. This process is repeated until an equilibrium is found where neither level has an incentive to change their selection. The entire bilevel formulation is outlined in (1)–(18).

2.1.1   Design – Upper level problem

The upper level's objective function in (1) minimizes the annualized investment cost of the new DERs (first and second terms) and the annual operational cost of the microgrid (third term) over the planning horizon. Here, the decision variables are the capacity (x_i) of each DER option to be installed. The total cost is converted into its present value by a factor γ, with ϱ_y being the capital recovery factor.[1] The objective function is constrained by a budget allocation (2) and the maximum available capacity of each DER (3).

$$\min_{x \geq 0} \gamma \sum_{y \in Y} \left\{ \varrho_y \left(\sum_{i \in \bar{B}} C_i^c x_i + \sum_{i \in S} C_i^c x_i \right) + \sum_{t \in T} C_y(t) \right\} \tag{1}$$

subject to

$$\sum_{i \in \bar{B}} C_i^c x_i + \sum_{i \in S} C_i^c x_i \leq \sum_{i \in B} C_i^b \tag{2}$$

$$x_i \leq X_i^{\max} \qquad \forall i \in B \tag{3}$$

2.1.2   EMS – Lower level problem

The formulation of the lower level problem, equivalent to an EMS solving an economic dispatch problem in a given time period t, is given by (4)–(18). The objective function defined by (4) minimizes the hourly operational cost in period t, given fuel and emission costs (first term), the costs of providing heat from a non

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[1] By definition, the capital recovery factor in year y is $\varrho_y = [r(r+1)^y]/[(r+1)^y - 1]$, where r is the annual interest rate. Moreover, $\gamma = [1 - (r+1)^{-J}]/r$ is used to bring all annual values to the present, where J is the length of the planning horizon in years.

CHP resource (second term), the maintenance cost of the new DERs as well as the existing units (third and fourth terms, respectively).

$$C_y(t) = \arg \min_P \sum_{i \in G} (C_i^f + C_i^z) \mu_i P_i^e(t)$$
$$+ \sum_{i \in Q} (C_i^f + C_i^z) \mu_i P_i^h(t)$$
$$+ \sum_{i \in B} C_i^m x_i + \sum_{i \in A} C_i^m a_i \tag{4}$$

The lower level's objective is constrained by hourly generation and load balance, (5) and (6), while both thermal and electrical loads are considered. Further details of the load model considered for the purposes of this work are provided in Section 4. which addresses a case study. The electrical power balance is

$$\sum_{i \in E} P_i^e(t) = L^e(t) \qquad ; \ \lambda(t) \tag{5}$$

while the thermal power balance requires

$$\sum_{i \in H} P_i^h(t) = L^h(t) \qquad ; \ \phi(t) \tag{6}$$

where $\lambda(t)$ and $\phi(t)$ are the Lagrange multipliers associated with those constraints.[2]

The hourly dispatch problem is further constrained by maximum and minimum limits of the dispatchable generating resources, (8) and (9). Other DERs considered in here are CHP units, wind power generation and energy storage systems. Modeling of the operational output of the combined heat and power unit is similar to that of a diesel generating unit. However, a CHP provides both electric power and useful thermal energy with a single fuel. The relationship between the thermal and electric load is shown in (7); readers are encouraged to refer to [19] for further details on CHP modeling. Wind generation is non-dispatchable and modeled as outlined in [18]. The capacities of the potential DERs x_i, passed by the upper level, serve as a maximum limits of the operational output of these resources as found in (9). The heat output from the CHP is given by

$$P_i^h(t) = \frac{P_i^e(t)}{\varsigma_i(t)}, \qquad\qquad \forall i \in N \ ; \ \omega_i(t) \tag{7}$$

and the generation limits are

$$P_i^{\min} \le P_i^e(t) \le P_i^{\max} \qquad\qquad \forall i \in D \ ; \ \alpha_i^{\min}(t), \alpha_i^{\max}(t) \tag{8}$$
$$0 \le P_i^e(t) \le x_i \qquad\qquad \forall i \in \bar{B} \ ; \ \delta_i^{\min}(t), \delta_i^{\max}(t) \tag{9}$$

General equations describing the operation of the storage system and its constraints are provided in (10)–(12). The variation of the state of charge (E_i) (10) depends on the charging/discharging power, the charging and discharging efficiency, and the storage capacity of the system. The maximum available energy (11) is constrained by the designed capacity passed by the upper level problem. The charging and discharging power limits of the storage device are outlined in (12). The constant v_i in (12) is dependent on the type of storage technology installed. A larger v_i suggests a faster charging and discharging storage device and vice versa.

$$E_i(t) = E_i(t-1) + \eta P_i(t) \Delta t \qquad\qquad \forall i \in S; \rho_i(t) \tag{10}$$
$$0 \le E_i(t) \le x_i \qquad\qquad \forall i \in S; \pi_i^{\min}(t), \pi_i^{\max}(t) \tag{11}$$
$$-v_i x_i \le P_i(t) \le v_i x_s \qquad\qquad \forall i \in S; \xi_i^{\min}(t), \xi_i^{\max}(t) \tag{12}$$

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[2]All Greek letters appearing to the right of semicolons in optimization problem constraints represent Lagrange multipliers of the respective constraints presented along the length of the paper.

Similarly, the dispatch problem is also subject to limits on energy available for both the electrical (13), (14) and thermal demand response resources (16), (17). Equations (15) and (18) outline the constraint on the hourly electric and thermal power available for DR respectively. Note that parameters k_r^e and k_r^h are dependent on the DR technology/strategy used. The electric-side demand response has to satisfy

$$E_r^e(t) = E_r^e(t-1) + P_r^e(t)\Delta t \quad ; \sigma(t) \tag{13}$$

$$0 \leq E_r^e(t) \leq w_r^e L^{e,\max} \qquad ; \tau^{\min}(t), \tau^{\max}(t) \tag{14}$$

$$-k_r^e w_r^e L^{e,\max} \leq P_r^e(t) \leq k_r^e w_r^e L^{e,\max} \quad ; \varphi^{\min}(t), \varphi^{\min}(t) \tag{15}$$

and the thermal load is flexible according to

$$E_r^h(t) = E_r^h(t-1) + P_r^h(t)\Delta t \quad ; \beta(t) \tag{16}$$

$$0 \leq E_r^h(t) \leq w_r^h L^{h,\max} \qquad ; \theta^{\min}(t), \theta^{\max}(t) \tag{17}$$

$$-k_r^h w_r^h L^{h,\max} \leq P_r^h(t) \leq k_r^h w_r^h L^{h,\max} \quad ; \psi^{\min}(t), \psi^{\max}(t) \tag{18}$$

2.2   Transformation to MPEC and MILP

Bilevel problems are usually difficult to solve; even the linear bilevel problem is an NP-hard problem [12]. Nevertheless, the aforementioned bilevel formulation for the microgrid combined planning and EMS problems can be transformed into a single level problem and solved jointly, provided the lower level's rational reactional set is non empty and its inducible region is a singleton [12]. With the linearization of the generation cost function and an assumed constant charging and discharging efficiency of the storage device, for each value of the upper level variable x_i, the lower level problem is proven to be linear (thus convex) as parametrized in x_i, $\forall i \in B$. Hence, there are two options in solving this problem

1. KKT formulation: to replace each lower-level problem by its corresponding Karush-Kuhn-Tucker (KKT) conditions.
2. Primal-dual formulation: to replace each lower-level problem by its primal constraints, its dual constraints, and by enforcing the strong duality theorem (SDT) equality.

The primal-dual approach has been demonstrated in [12], [13] to be more efficient than the KKT option. The complementary slackness present in the KKT approach is eliminated in the second formulation via the strong duality theorem in which the primal and the dual objective functions are equated. Given that, we take the primal-dual approach in this work. The transformation, as outlined below, comprises replacing the lower level problem with the its constraints (5)–(18) and its dual constraints (22)–(32). This is combined with the equality associated with the SDT (33) and the upper level problem (2), (3) to make up the transformed MPEC.

$$\min_{x \geq 0}(1) \tag{19}$$

subject to

$$\text{Constraints (2)–(3)} \tag{20}$$

$$\text{Constraints(5)–(18)} \tag{21}$$

dual constraints

$$C_i^f + C_i^z - \lambda(t) - \alpha_i^{\min}(t) + \alpha_i^{\max}(t) = 0 \qquad \forall i \in D \tag{22}$$

$$C_i^f + C_i^z - \lambda(t) - \delta_i^{\min}(t) + \delta_i^{\max}(t) - \frac{\omega_i(t)}{\varsigma_i(t)} = 0 \qquad \forall i \in N \tag{23}$$

$$-\lambda(t) - \delta_i^{\min}(t) + \delta_i^{\max}(t) = 0 \qquad \forall i \in W \tag{24}$$

$$-\lambda(t) - \xi_i^{\min}(t) + \xi_i^{\max}(t) - \rho_i(t) = 0 \qquad \forall i \in S \tag{25}$$

$$-\rho_i(t) - \pi_i^{\min}(t) + \pi_i^{\max}(t) = 0 \qquad \forall i \in S \tag{26}$$

$$-\lambda(t) - \varphi^{\min}(t) + \varphi^{\max}(t) - \sigma(t) = 0 \tag{27}$$

$$-\tau^{\min}(t) + \tau^{\max}(t) - \sigma(t) = 0 \tag{28}$$

$$-\phi(t) - \psi^{\min}(t) + \psi^{\max}(t) - \beta(t) = 0 \tag{29}$$

$$-\theta^{\min}(t) + \theta^{\max}(t) - \beta(t) = 0 \tag{30}$$

$$-\phi^{\min}(t) + \omega_i(t) = 0 \tag{31}$$

$$C_i^f - \phi(t) = 0 \qquad\qquad \forall i \in H \tag{32}$$

and the strong duality equality

$$\begin{aligned}
&\sum_{i \in G}(C_i^f + C_i^z)\mu_i P_i^e(t) + \sum_{i \in Q}(C_i^f + C_i^z)\mu_i P_i^h(t) = \lambda L^e(t) + \sum_{i \in D}(\alpha_i^{\min}(t)P_i^{\min} - \alpha_i^{\max}(t)P_i^{\max}) \\
&- \sum_{i \in \bar{B}}\delta_i^{\max}(t)x_i - \sum_{i \in S}(v_i\xi_i^{\min}(t)x_i + v_i\xi_i^{\max}(t)x_i) - \sum_{i \in S}(\pi_i^{\max}(t)x_i - \rho_i(t)E_i(t-1)) \\
&+ \sigma(t)E_r^e(t-1) - w_r^e\tau^{\max}(t)L^{e,\max} - (\varphi^{\min}(t)k_r^e w_r^e L^{e,\max} + \varphi^{\max}(t)k_r^e w_r^e L^{e,\max}) \\
&+ \phi(t)L^h(t) + \beta(t)E_r^h(t-1) - \theta^{\max}(t)w_r^h L^{h,\max} - (k_r^h w_r^h \psi^{\min}(t)L^{h,\max} + k_r^h w_r^h \psi^{\max}(t)L^{h,\max}) \tag{33}
\end{aligned}$$

The non-linearities associated with the products of variables $\delta_i^{\max}x_i$, $v_i\xi_i^{\max}x_i$, $v_i\xi_i^{\min}x_i$ and $\pi_i^{\max}x_i$ in (33) of this MPEC can be linearized at the expense of more constraints and auxiliary variables, transforming the problem into an equivalent MILP problem. An overview of the linearization of (33) is outlined in the Appendix. Note that all the Lagrange multipliers are positive variables here.

3 Case study

The proposed bi-level design approach is applied next to a microgrid implementation of a remote mine in northern Quebec, Canada. The energy infrastructure of remote mines is characterized by unique features that differentiate them from most remote community microgrids. A remote mine is an intensive energy user with rated load in the range of 5 MW to 650 MW depending on the type of product mined and the process employed [20]. Its load profile is often very steady with a little fluctuation over the course of a day. High reliability is required on these sites for worker safety and for economic reasons (auxiliary back-up is essentially indispensable). Load growth in most mines often occurs during the first few years of production as new sections of the operation are opened. Once a steady production is attained, load growth in subsequent years is unlikely. In addition, for most mines surface and sub-surface ventilation represent a base electrical load [10]. The adoption of ventilation on demand technology, however, allows these loads to be regulated, making it possible to implement demand response strategies.

The peak electric load of the mine considered here is 10 MW with an average load of 9.5 MW. This load is currently supplied by a 6 MW diesel generator and two smaller 2 MW units. Space heating at the mine site is provided by a gas-fired heat exchanger. The diurnal and annual daily heating and cooling profiles from [10, 21] are adapted for this work. Seven day type loads are considered in modeling the entire monthly load. These day types represent 5 weekdays and 2 weekend days in a week. They are aggregated by a factor based on the number of day types in a particular month. The weekly profile is then modeled for each and every month to reflect the seasonality in the year. Ten percent of the mine's electrical and heating load is assumed to be available for DR. The mine has been in operation for some years now so load growth is negligible. It is also known to have some level of control and communication devices already installed to regulate its load during emergencies; hence, additional costs to implement DR are negligible. The cost of diesel fuel delivered at the mine location is relatively high due limited transportation options for diesel. Fuel escalation rate based on historical pattern is also considered. The ESS technology considered is a new generation compressed air energy storage system with a ratio of energy storage capacity to power capacity of four hours. The hypothetical layout of the mine with some modification is provided in Figure 2.

Three planning scenarios are considered for expanding the energy infrastructure of the existing remote microgrid: i) the base case plus wind power generation, ii) the base case plus wind power generation and electrical energy storage, and iii) the base case plus wind power generation, energy storage and demand
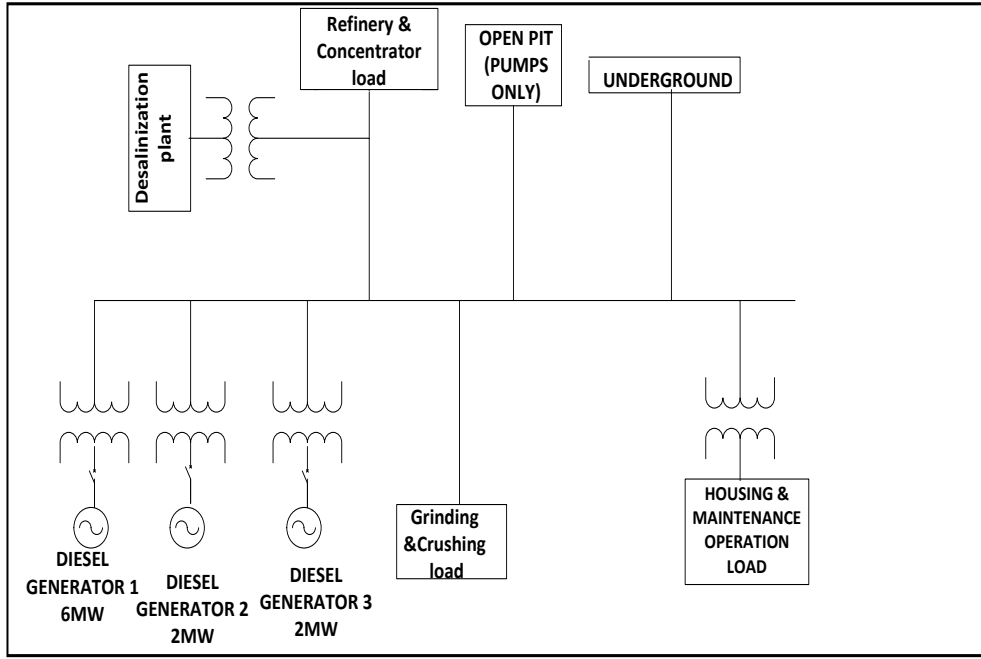
Figure 2: Schematic diagram of the remote mine energy generation infrastructure.

response. Economic parameters of the mine and other required data are provided in Table 1. Moreover, a capital cost allowance of 50% is considered for corporate tax purposes.

The cost associated with CO_2 emission (C_i^z) in this case, is determined by placing a carbon tax (in \$/ton) on a ton of CO_2 emitted by each generating resource i, considering their emission factor.

Table 1: Summary of input parameters

Diesel Generators		Wind Turbine	
Fuel cost (wholesale) [22]	0.76 \$/l	Capital Cost [25]	2213 \$/kW
Fixed O&M [22]	15 \$/kW/yr	Fixed O&M [25]	10 \$/kW/yr
Variable O&M [22]	3 \$/MWh	**Storage**	
Emission rate [23]	2.64 kg/l	Capital Cost [25]	600 \$/kW
CHP		**Financial Parameters**	
Capital Cost [19]	1200 \$/kW	Interest rate	3.5%
Natural Gas Cost [19]	3.1 \$/GJ	Planning horizon	20 years
O&M Cost [19]	0.006 \$/kWh	Carbon Tax [23]	30 \$/ton
		Escalation rate	3%

4 Results and discussion

4.1 Investment decisions

The above case study was evaluated using a custom-made Microsoft Excel tool interfacing with the CPLEX solver via GAMS, termed BIEX (BI-level EXcel). To validate the proposed approach, the results are compared with those of DERCAM (a commercially accepted software based on the traditional MILP) [3]. The output

designs of both approaches are shown in Table 2. Both tools were provided with the same input data and parameters to make the comparison reliable. From Table 2 it could be observed that the total cost (capital plus operating) of BIEX is lower than that of DERCAM, though their optimal configuration is comparably similar. This could be attributed to lower operation cost in BIEX due to the simultaneous optimization of operations and infrastructure design by the lower level EMS. The cost presented in Table 2 (last column) is the sum of the annualized investment costs of the design solution and annual the operational costs in k$.

Table 2: Optimal Microgrid Expansion

	Wind (kW)	CHP (kW)	Storage (kWh)	Cost (k$)
BIEX	3000	1047	1848	8117
DERCAM	3000	1000	1900	8792

4.2 EMS output

The performance of the EMS is presented in Figure 4 and Figure 5, while Figure 3 shows the hourly generation profile of the generating units in the base case. Figures 4 and 5 also show the electrical and thermal output of DERs set by the EMS in a typical day. It could be observed from Figure 3 that the mine often utilizes all its three generators in the base case while the third diesel unit (Diesel III) is kept constant at its maximum operating point. However, with the implementation of the EMS, the two smaller generators (*i.e.*, Diesel I and Diesel II) rarely operate resulting in significant savings. The output of the largest generator (Diesel III) is also seen to experience some level of fluctuation unlike in the base case. With high output from the wind turbine, less power needs to be provided by Diesel III and vice versa when the wind output is low. The ability of the EMS to take full advantage of the no-cost energy from the wind also contributes to the reduction in energy costs. The output of the heat exchanger is primarily dictated by the thermal need of the mine in the base case. Heat from the CHP also offsets parts of the energy extracted from the heat exchanger in other scenarios.

4.3 Financial performance metrics and results

Key financial metrics such as the Present Value Ratio (PVR) and the Internal Rate of Return (IRR) are used next in determining the profitability of the investment options. The PVR is the ratio of the present value
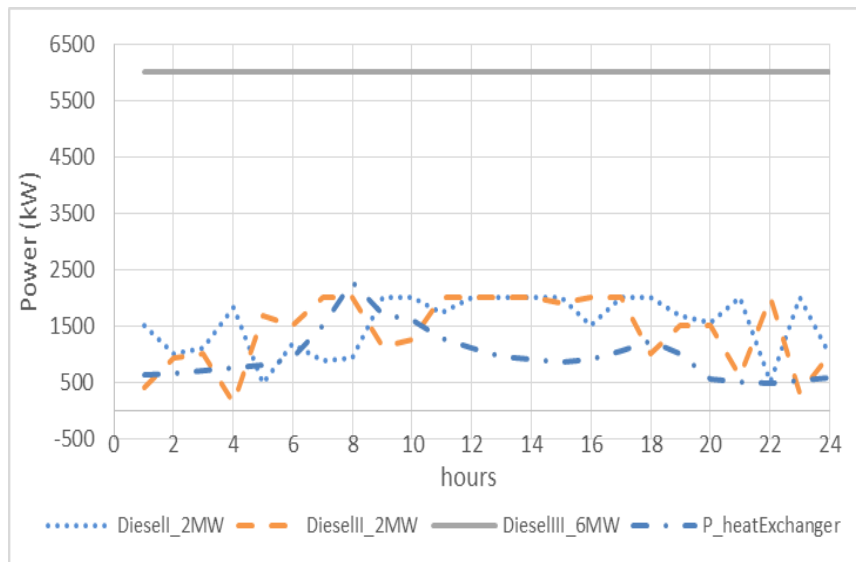

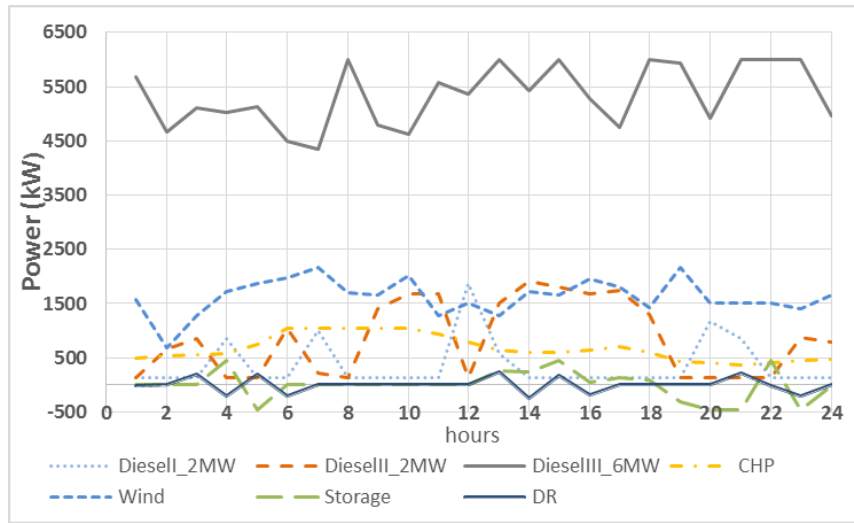Figure 3: Generating units operating point in a typical day.

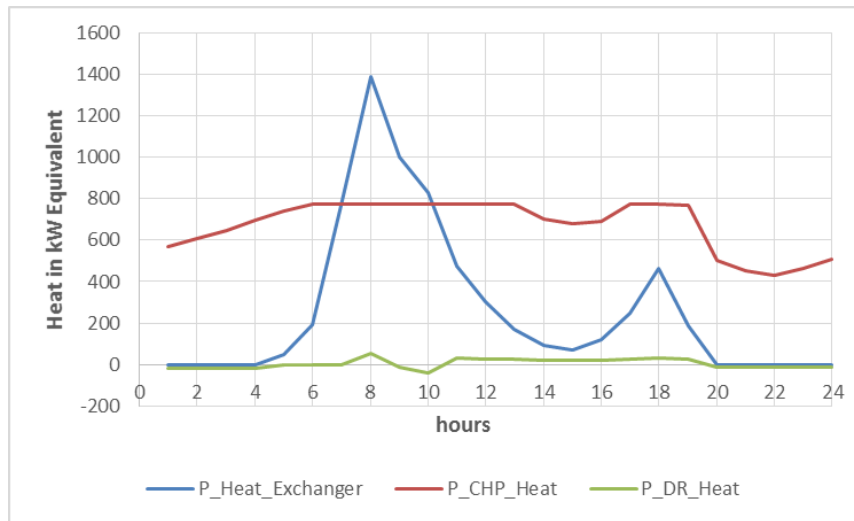Figure 4: Electrical output of DERs in a typical day.

Figure 5: Thermal output of DERs in a typical day.

(PV) of the microgrid benefit/revenue to the PV of the investment cost. A PVR greater than one indicates the profitability of an investment, which is unprofitable when its PVR less than one. We elaborate further on the IRR in a subsequent subsection.

The output of the bi-level planning strategy was subjected to cost benefit analysis. Results obtained show significant savings in energy costs for all three planning scenarios. Nevertheless, scenario iii) happens to yield the most benefit to all participating stakeholders. Table 3 outlines the outcome of the economic analysis for this scenario. It illustrates the benefit to cost ratio or PVR for the corresponding stakeholders, herein referred to as actors. The base unit corresponds to the base case total cost. High percentage of savings to the mines could be observed from Table 3. The reduced fuel costs due to a lower consumption of diesel coupled with the strategic optimization by the EMS contribute to the increase the mine's PVR.

Table 3: Costs and Benefits

Benefit	Basecase	Microgrid	Savings	PVR
Emission Cost	0.125	0.081	34.9%	
Fuel Cost	0.875	0.581	33.61%	
Investment Cost	0.000	0.046		
Total Cost	1.000	0.708		
Total Savings			29.22%	6.416

4.4 Sensitivity analysis

The planning process is now subjected to changes in factors likely to influence usual power system planning and operation to demonstrate the effectiveness of the approach.

4.4.1 Fuel escalation

The impact of fuel price changes is investigated in this subsection. The design approach was subjected to changes in fuel prices and the effect on the optimal configuration was observed. Figure 6 shows that as fuel prices increase the percentage of wind and storage capacities, that makes up the optimal solution, increases until they reach their maximum capacity of 3000 kW and 500 kW, respectively. Their percentage also decreases with decreasing fuel prices while that of the CHP decreases with increasing fuel prices and vice versa. In demonstrating the technological neutrality of the proposed strategy, a diesel generator was included as one of the potential DER options to be installed. However, from Figure 6 it could also be observed that no new diesel capacity was added, even at low fuel cost. This due to the premium placed on the extra emissions associated with this option. Furthermore, it is also observed that the PVR decreases with reduction in fuel cost till 0.11 p.u. (where the PVR equals 1, indicating the breakeven point). The current price of fuel is equivalent to 1 p.u. on the horizontal axis. Table 4 also shows the design solution of the optimal case with a annual fuel escalation rate of 3%.

4.4.2 Load growth

The study here also considers the effect of load growth on the planning strategy. It is observed that, with an annual growth of 2% in load, higher savings are observed, in particular in the third microgrid scenario. In
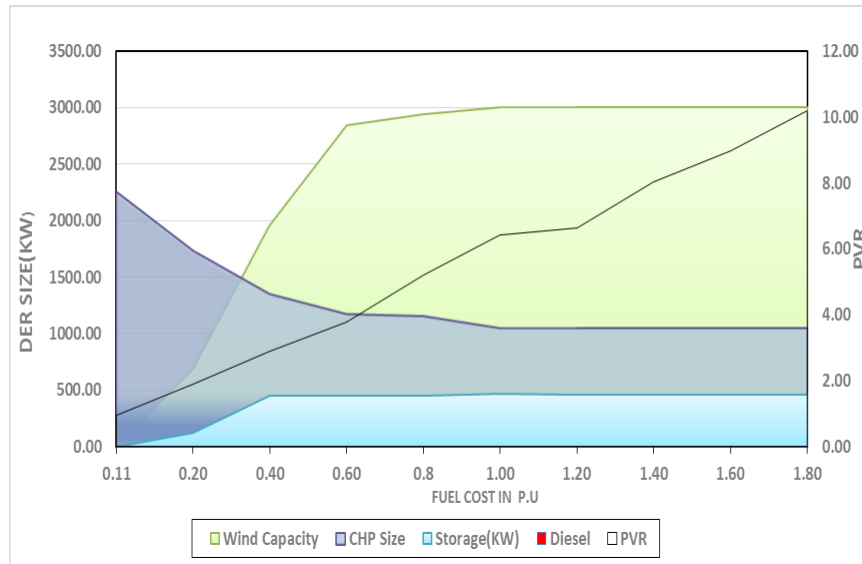

Figure 6: DER sizes with change in fuel price.

Table 4: Optimal Microgrid Expansion with Fuel Price Increase of 3% per Year

Wind (kW)	CHP (kW)	Diesel (kW)	Storage (kWh)	Storage (kW)
3000	1811	0	2000	500

addition, the optimal design solution presented higher capacities of DERs to be installed as shown in Table 5. It should be noted that the maximum rating of the resources were modified to accommodate the load growth over 25 years.

Table 5: Optimal Microgrid Expansion with Load Growth of 2% per Year

Wind (kW)	CHP (kW)	Storage (kWh)
5000	3000	2600

4.4.3   Savings on assets

As observed in Figure 4, the two smaller generators, Diesel I and II, are hardly utilized when the proposed strategy is implemented. Thus, one of the smaller generators was completely taken out and the effect on the design solution, as well as the profitability of the investment, was monitored. Table 6 shows that there were slight changes in the design solution and an increase in the PVR value. This implies the possibility of making savings on a generator asset without significantly compromising on the optimal design solution. Without considering revenue from the sale of the asset, an increase of 25.57% in the profitability of the design solution is observed when compared to the solution in Table 2 .

Table 6: Optimal Microgrid Expansion with Diesel I Unit Decommissioned

Wind (kW)	CHP (kW)	Storage (kWh)	PVR	Diff. (%)
3000	1520	2220	8.02	25.57

4.4.4   Project internal rate of return (IRR)

The discount rate was varied to determine the interest rate at which an investment in expanding this mining microgrid would breakeven. A high IRR of 21.5% was obtained, which suggests the attractiveness of implementing a DER rollout in a remote mining context. This would be especially the case for potential investors in areas with competitive borrowing rates. This makes microgrid development an attractive investment option in these jurisdictions, especially with low-carbon generation technologies. It is worth noting that no reinvestment is considered in computing the IRR.

5   Conclusion

A bilevel optimization formulation for a microgrid planning problem has been developed and implemented in this work. The coupled planning and operational problem is recast as an MPEC and transformed into an MILP based on the strong duality theorem. The transformed MILP simultaneously determines the design configuration and optimally allocates the DERs through the implementation of an EMS proxy whose role is to dispatch the resources in real time. Results obtained from the implementation of the proposed approach for the specific case of a remote mine are compared to those of a commercial MILP-based microgrid planning software. A comparison of the results of the two optimization tools (commercial tool and the proposed approach) showed lower total energy cost in the proposed approach, which do end up outweighing the extra DER capacity investments made. The results also demonstrate how a microgrid with an enabling technology mix of DERs and an EMS based on advanced optimization strategy could be crucial in achieving a higher

returns on investment. The high IRR found in the paper's case study indicate the attractiveness of microgrids based on sustainable low-carbon DERs to potential investors and participating stakeholders.

Future work in this area includes the consideration of non-industrial remote communities where load factors are much lower. It would be of interest to determine how the optimal DER investment mix is affected by the peakedness of the load. At the same time, it would be of interest to assess several energy storage technologies depicting different rated energy to rated power ratios.

Appendix A. Linearization of the strong duality equality

The strong duality equality (33) includes four nonlinear expressions: $\delta_i^{\max} x_i$, $v_i \xi_i^{\max} x_i$, $v_i \xi_i^{\min} x_i$ and $\pi_i^{\max} x_i$. The first nonlinearity is linearized as in (34)–(36) where $X_i^{\max}$ is the maximum available capacity of resource i.

$$z_i = \delta_i^{\max} x_i, \qquad \forall i \in \bar{B} \tag{34}$$
$$0 \le z_i \le \delta_i^{\max} X_i^{\max}, \qquad \forall i \in \bar{B} \tag{35}$$
$$x_i - (1 - \delta_i^{\max}) X_i^{\max} \le z_i \le x_i, \qquad \forall i \in \bar{B} \tag{36}$$

The other nonlinear expressions are linearized based on the same concept and are not repeated for brevity.

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