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Abstract: This paper proposes a hierarchical decision making model for a coupled planning and operation problem of an advanced microgrid. The proposed model, is formulated as a bilevel optimization problem and recast as a mathematical program with equilibrium constraints (MPEC) where the decision variables of the two problems are independently controlled. The upper problem determines the strategic investment decision and optimal configuration of the microgrid, the needs for carbon emission permits and peak charges from using neighbouring network capacity, while the lower problem optimizes the output of the distributed energy resources (DER) through the implementation of an energy management system (EMS). The proposed approach was applied to the energy infrastructure of a remote mine. Results obtained through its application show significant savings in the cost of energy and improved benefits to stakeholders. They also show the advantages of a bilevel approach over other state-of-the-art microgrid planning methodologies.

Keywords: Bilevel optimization, economic analysis, energy management, distributed energy resources, microgrid planning

Résumé :   Cet article propose un modèle de planification hiérarchique capable d'effectuer de manière systématique le lien entre les exigences opérationnelles et de conception d'un micro-réseau électrique. Le problème de planification intégré est formulé tel un problème d'optimisation bi-niveaux qui est, par la suite, reformulé tel un problème de programmation mathématique sous contrainte d'équilibre. On démontre que la formulation bi-niveaux est appropriée étant donné que les variables de décision au niveau stratégique ne sont pas directement alignées avec celles du niveau opérationnel. Concrètement, c'est au niveau supérieur que les décisions stratégiques d'investissements, de conception, de gestion des permis d'émission de carbone et d'utilisation de ressources énergétiques exogènes sont arrêtées. De son côté, le niveau inférieur procède à la programmation opérationnelle du micro-réseau via l'exploitation de ses ressources énergétiques. On applique cette approche à un cas de mise à niveau de l'infrastructure énergétique d'une exploitation minière éloignée. Les résultats obtenus démontrent comment l'approche proposée permet de réduire les charges d'exploitation tout en générant d'autres bénéfices pour les différents acteurs du système. On y voit aussi comment l'approche bi-niveaux est avantageuse comparativement à d'autres méthodes de planification des micro-réseaux.

Mots clés :   Optimisation bi-niveaux, analyse économique, gestion de l'énergie, programmation opérationnelle des ressources énergétiques, planification des micro-rseaux

Nomenclature

The main symbols used in the paper are listed below:

Indices

i Index for all energy resources

t Index for hour

h Superscript for heat/thermal resources

e Superscript for electrical resources

y Index for years of project lifetime

r Index of demand response (DR)

Sets

B Set of indices for 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 combined heat and power (CHP) units

Q Set of non-CHP gas fired thermal units

S Set of electrical energy storage (ESS) devices

U Set of remote community power resources

W Set of indices of wind power generating units

Y Set of indices of years in the project lifetime J

T Set of indices of time t within a year

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 of resource i

C_i^u Cost of purchased energy from remote community power resource i

C_y^z Cost of carbon permit per kg CO_2 in year y

C_i^m Maintenance cost for resource i

$X_i^{\max}$ Maximum power capacity 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

$L^e(y,t)$ Electrical load at time t in year y

$L^h(y,t)$ Thermal load at time t in year y

$L^{e,\max}$ 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

Operation level Variables

$P_i^e(y,t)$ Electrical output of resource i at time t in year y

$P_i^h(y,t)$ Thermal output of resource i at time t in year y

$P_r^e(y,t)$ Electrical output from DR at time t in year y

$P_r^h(y,t)$ Thermal output from DR at time t in year y

$E_i^e(y,t)$ Electrical energy level of ESS i at time t in year y

Design Level Variables

$\mathcal{R}_y^p$ Peak power drawn from neighbouring community resources in year y

x_i Capacity of DER assets to be installed

Υ_y Carbon permits bought in year y

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 (DERs) to compliment central grid infrastructures. Government policies, technological advancement, economic and environmental incentives are changing the features of power systems, while DERs gradually increase their presence. Many key industrial players have developed energy saving strategies and are investing in renewable energy.

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 DERs within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid [1]. It can operate connected to the grid or in isolation. Nevertheless, the microgrid concept and functionalities have evolved over the years from providing emergency energy supply for reliability to include an energy management system (EMS) that should optimally allocate energy resources to minimize cost. The concept and its changing functionalities characterizing advanced microgrids are described in detail in [2]. It is clear that the successful implementation of advanced microgrids will require advance planning strategies to best capture operational and financial benefits.

1.1   Literature review

Most research work reported in literature on microgrid planning and operation tends to decouple the investment planning problem from the microgrid operational problem. The literature here can be categorized into three groups.

The first category pertains to microgrid operational planning challenges. Papers within this group assume a known microgrid design capacity/configuration, and they propose different optimization algorithms to minimize the systems' operational cost considering environmental and reliability implications [3]–[13]. Their applications span remote networks all the way to industrial applications. Recent publications within this group have focused on energy management strategies that deal with supply/demand uncertainties and highlight the value of flexible resources within the network [6]–[8].

From the planning perspective, the second category of contributions proposed planning problem formulations seeking to configure and size the assets of microgrids. The design problem formulations here are generally presented either as single or as multiobjective optimization problems [14]–[18]. Each of them has a generic cost minimization objective with some variations around constraints, objective functions and available technologies. Specifically, the proposed approach in [14] 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, while a benefit to cost ratio is also considered in [16] for determining the best planning option. Complex, cumbersome and costly fuel logistics unique to several remote networks are also highlighted in [18] where heuristics are used to establish the microgrid design.

The third category of contributions, within which this paper belongs, investigates joint microgrid design and operations [19]–[21]. Particularly, in [19], authors have developed a two-step mixed-integer linear programming (MILP) model that optimizes the configuration of a hybrid microgrid and seeks to determine an operating policy based on the design. The first step solves an MILP to select and size the microgrid assets, while this solution is then passed to a second step where a data mining analysis is used to establish the logic of a microgrid controller. Also, a bilevel optimization design approach for ESS sizing in microgrids is proposed in [20] where the upper level's objective of minimizing cost and the lower level's variable operation cost are aligned [20]. The authors of [21] also attempt to nest the microgrid planning and operational problem in

the form of a generalized doubleshell framework based on an evolutionary algorithm; however, the economic analysis of the design options in [21] are not established systematically.

1.2 Gaps in the state-of-the-art and contributions

From the above survey, it can be concluded several challenges must be addressed when considering joint microgrid asset and operations planning, as this paper does. Specific gaps include 1) the need to include the widest range of asset classes for system designers, 2) the need to design multi-energy microgrids systematically, and 3) to formulate joint optimal design-operation problems that represent with better fidelity the actual flow of decision making and that can exploit the capabilities of available high-performance MILP solvers.

This paper addresses these challenges by proposing a design approach for microgrids acknowledging the wide array of technologies available to microgrid designers: generation (to installed in the microgrid and/or to be obtained from a neighbouring community power system), energy storage system (ESS), combined heat and power (CHP), and demand response (DR). All these can represent their operations with good fidelity over a microgrid's lifetime. The high-fidelity operational representation is enabled by the formulation of the problem as a bilevel optimization problem, which can be solved systematically by commercially available MILP solvers. At the same time, the design problem formulation allows microgrid planners to consider coupled heat and power demands systematically. As a side benefit, the formulation of the microgrid planning problem we cast here is capable of providing decision support to operators who can take advantage of periodically updating asset configurations, given changing operating conditions e.g., cost saving seasonal decommissioning/idling diesel generation.

To demonstrate the design approach, an extensive case study is developed for the upgrade of heat and power generation infrastructure of a remote mine. The design and operational performance results are shown to outperform the widely-accepted, industry microgrid design software tool DERCAM [14]. The approaches in [22] and [23] are further exploited to provide an economic justification for different investment options.

The rest of the paper is structured as follows: Section II outlines the proposed bilevel formulation and its transformation into an equivalent mathematical program with equilibrium constraints (MPEC) followed by a second transformation into an MILP problem to be solved by commercial solvers. Section III outlines an economic analysis of the planning options. Section IV then describes an application of the proposed formulation to a representative remote mining operation, and Section V discusses the results obtained. Section VI finally provides brief concluding remarks.

2 Problem formulation

When choosing and sizing the microgrid components, a reflection of the expected system operations must appear within the design problem. At the same time, it is clear that past microgrid design decisions can have a direct incidence upon operating costs and the available operating space. Therefore, there is a need to find a way to unify these two with the objective of finding the *best microgrid design*, which could provide the *best operating conditions* over the microgrid assets' lifetimes, *i.e.*, an overall profitable business case. At the same time, it is important to represent with better fidelity the fact that in practice design and operating decisions are made sequentially and without direct cooperation. This sequentiality and non-cooperation have an incidence on design and operating decisions, even in spite of the fact that design and operating objectives are aligned. It is just unrealistic to assume that operating decisions for the entire lifetime of a microgrid can be programmed at the same time as the microgrid is designed.

The process where the design of a microgrid is established in this fashion could be cast as a sequence of interactions where the designer proposes a microgrid configuration with the objective of minimizing the combined cost of strategic decisions on investment, power purchases from neighbouring systems and an estimate of carbon permits' cost. Given the proposal of the designer, the operator is then to minimize the microgrid running costs. The designer, observing the operator's actions, could then set a new design which the operator would then work with. This process could go on until the designer and operator find an equilibrium (fixed point) where neither of them has an incentive to change their decisions.

The above description of a repeated interaction can be recast as a bilevel optimization problem [24]. The designer is primarily tasked with reducing the capital investment costs; this requires the designer's main objective to have just enough capacity to meet the operating requirements while considering uncertain market prices. On the other hand, the operator can benefit from having wider margins and flexibility to reduce operating costs; such operational improvements can only come at the expense of further capital expenditures incurred at that upper level. As mentioned above, such an approach could be equally extended to study opportunities for periodic asset reconfiguration and maintenance planning, since it can trade off respective costs and benefits of planning and operations.

2.1 Bilevel model outline

The sequential 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 microgrid EMS (operator proxy) acting 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 rates and budget constraints. It then selects a design configuration (capacity of DERs, $x_i, \forall i \in B$, where B is the set of all DER options; power capacity purchases with a neighbouring system $\mathcal{R}_i \ \forall i \in U$) 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 region of the lower level problem. The EMS thus determines the operating points of the DERs minimizing hourly running costs based on the parameters received. The DER set points (P_i) are passed back to the upper level to evaluate the total cost over the 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 its selection. The entire bilevel formulation is outlined in (1)–(19).
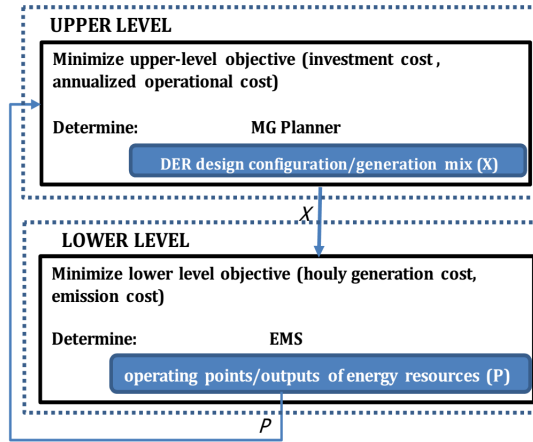

Figure 1: Schematic diagram of the bilevel design-operating model.

2.1.1 Business case & 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 demand charge by the remote community energy provider (third term) and the cost of allowable carbon permits (fourth term). The variable (x_i) denoting the capacities of each DER option to be installed is the solution to the upper level's problem. The total planning 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 for investment (2) and the maximum allowable carbon permits purchased (3). The

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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.

parameter ζ_i denotes CO_2 emitted by resource i per kWh.

$$\min_{x,\mathcal{R},\Upsilon\geq 0} \gamma \sum_{y\in Y} \left\{ \varrho_y \left(\sum_{i\in\bar{B}} C_i^c x_i + \sum_{i\in S} C_i^c x_i \right) + C_y^u(\mathcal{R}_y^p) + C_y^z(\Upsilon_y) \right\} \tag{1}$$

subject to

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

$$\sum_{i\in D}\sum_{t\in T} \zeta_i \mu_i P_i^e(y,t) + \sum_{i\in Q}\sum_{t\in T} \zeta_i \mu_i P_i^h(y,t) \leq \Upsilon_y \tag{3}$$

where $\mathcal{R}_y^p$ is the peak power drawn in year y from the neighbouring remote community energy provider resources ($i \in U$) and given by (4) for all $t \in T$

$$\mathcal{R}_y^p \geq P_i^e(y,t) \tag{4}$$

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 (5)–(19). The objective function defined by (5) minimizes the hourly electrical generation cost in period t (first term), the costs of providing heat from a non-CHP resource (second term), the cost of electric energy from the neighbouring remote community provider (third term), the maintenance cost of the new DERs as well as the existing units (fourth and fifth terms, respectively).

$$(P_i^e(y,t), P_i^h(y,t)) = \arg\min_{P^e,P^h} \sum_{i\in G} C_i^f P_i^e(y,t) + \sum_{i\in Q} C_i^f P_i^h(y,t)$$
$$+ \sum_{i\in U} C_i^u P_i^e(y,t) + \sum_{i\in B} C_i^m x_i + \sum_{i\in A} C_i^m a_i \tag{5}$$

The lower level's objective is constrained by hourly electrical and thermal generation and load balances, (6) and (7). The electrical power balance for all hours $t \in T$ and years $y \in Y$ is

$$\sum_{i\in E} P_i^e(y,t) + \sum_{i\in U} P_i^e(y,t) = L^e(y,t); \qquad \lambda(y,t) \tag{6}$$

while the thermal power balance requires also for each hour t of all years y

$$\sum_{i\in H} P_i^h(y,t) = L^h(y,t); \qquad \phi(y,t) \tag{7}$$

where $\lambda(y,t)$ and $\phi(y,t)$ 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, (9). Other DERs considered here are CHP units, wind turbines and ESS. 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 from a single fuel. The relationship between the thermal and electric load is shown in (8); readers are encouraged to refer to [25] for further details on CHP modeling. Wind generation is non-dispatchable and the uncertainty associated with its speed is modeled based on the Weibull distribution function as outlined in [23], [26]. Energy from storage technologies available within the microgrid are also used to mitigate the deviation of wind from its forecasted values. 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 (10). The heat output from the CHP is given by

$$P_i^h(y,t) = \frac{P_i^e(y,t)}{\varsigma_i}; \qquad \omega_i(y,t) \tag{8}$$

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

for all $i \in N$, $t \in T$ and $y \in Y$. The generation limits are

$$P_i^{\min} \leq P_i^e(y,t) \leq P_i^{\max}; \qquad\qquad \alpha_i^{\min}(y,t), \alpha_i^{\max}(y,t) \qquad\qquad (9)$$

for all $i \in D$, $t \in T$ and $y \in Y$, in addition

$$0 \leq P_i^e(y,t) \leq x_i; \qquad\qquad \delta_i^{\min}(y,t), \delta_i^{\max}(y,t) \qquad\qquad (10)$$

for all $i \in \bar{B}$, $t \in T$ and $y \in Y$.

General equations describing the operation of the ESS and its constraints are provided in (11)–(13). The variation of the state of charge (SOC) E_i in (11) depends on the charging/discharging power, the charging and discharging efficiency, and the storage capacity of the system. The maximum available energy (12) is constrained by the design capacity passed by the upper level problem. The charging and discharging power limits of the storage device are outlined in (13). The constant v_i in (13) is dependent on the type of storage technology installed. A larger v_i suggests a faster charging and discharging storage device and vice versa. Here, for each ESS resource $i \in S$, hours $t \in T$ and years $y \in Y$.

$$E_i(y,t) = E_i(y,t-1) + \eta P_i(y,t)\Delta t; \qquad\qquad \rho_i(y,t) \qquad\qquad (11)$$
$$0 \leq E_i(y,t) \leq x_i; \qquad\qquad \pi_i^{\min}(y,t), \pi_i^{\max}(y,t) \qquad\qquad (12)$$
$$-v_i x_i \leq P_i(y,t) \leq v_i x_i; \qquad\qquad \xi_i^{\min}(y,t), \xi_i^{\max}(y,t) \qquad\qquad (13)$$

Similarly, the dispatch problem is also subject to limits on energy available for both the electrical (14), (15) and thermal demand response resources (17), (18). Equations (16) and (19) outline the constraint on the hourly electric and thermal power available for DR respectively. Note that parameters $k_{y,r}^e$ and $k_{y,r}^h$ are dependent on the DR technology/strategy used. The electric-side demand response has to satisfy

$$E_r^e(y,t) = E_r^e(y,t-1) + P_r^e(y,t)\Delta t; \qquad\qquad \sigma(y,t) \qquad\qquad (14)$$
$$0 \leq E_r^e(y,t) \leq w_r^e L^{e,\max}; \qquad\qquad \tau^{\min}(y,t), \tau^{\max}(y,t) \qquad\qquad (15)$$
$$-k_r^e w_r^e L^{e,\max} \leq P_r^e(y,t) \leq k_r^e w_r^e L^{e,\max}; \qquad\qquad \varphi^{\min}(y,t), \varphi^{\min}(y,t) \qquad\qquad (16)$$

and the thermal load is flexible according to, for all $t \in T$ and $y \in Y$,

$$E_r^h(y,t) = E_r^h(y,t-1) + P_r^h(y,t)\Delta t; \qquad\qquad \beta(y,t) \qquad\qquad (17)$$
$$0 \leq E_r^h(y,t) \leq w_r^h L^{h,\max}; \qquad\qquad \theta^{\min}(y,t), \theta^{\max}(y,t) \qquad\qquad (18)$$
$$-k_r^h w_r^h L^{h,\max} \leq P_r^h(y,t) \leq k_r^h w_r^h L^{h,\max}; \qquad\qquad \psi^{\min}(y,t), \psi^{\max}(y,t) \qquad\qquad (19)$$

We note that uncertainty in operations—*e.g.*, coming from uncertain wind and solar generation—could be considered by having several operating scenarios at the lower level. Concretely, this would turn the problem into a single-leader, multiple-follower bilevel problem, where each low-level follower would optimize its operations based on its given operating scenario for the common microgrid configuration provided by the leader. The upper-level leader's task would be to configure the microgrid based on probability-weighted operating costs coming from the low-level operating scenarios. This way, the designer would get to find a compromise between the need minimize the costs of the "average" operating scenario, while also appraising the value of being able to operate adequately for low-probability scenarios. We note, nonetheless, that the main downside of this would be the multiplication of lower-level variables and constraints by the number of scenarios considered.

2.2   Co-linearity and justifying a bilevel planning approach

Bilevel programming problems are closely related to multiobjective (and multistage) optimization problems. This relation has been illustrated in [27] and can be observed considering[3] the bilevel problem $\mathcal{B}$, which consists of (20)–(23), and the multiobjective problem $\mathcal{M}$, (24)–(26):

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[3]The variables used here are for illustrative purposes and do not relate to the problem at stake in this paper.

$$(\mathcal{B}) \qquad \min_{x,y} cx \qquad\qquad\qquad (20)$$

subject to

$$y = \arg\min_{y}(dx + fy) \qquad\qquad\qquad (21)$$

$$Ax + By \le a \qquad\qquad\qquad (22)$$

$$Cy \le b \qquad\qquad\qquad (23)$$

and

$$(\mathcal{M}) \qquad \min_{x,y} cx + dx + fy \qquad\qquad\qquad (24)$$

subject to

$$Ax + By \le a \qquad\qquad\qquad (25)$$

$$Cy \le b \qquad\qquad\qquad (26)$$

Here, it is easy to observe that a solution of the bilevel programming problem $\mathcal{B}$ is Pareto optimal for the corresponding multiobjective optimization problem $\mathcal{M}$ if $c = \xi d$, where $\xi > 0$, and $c, d \in \mathbb{R}^n$. Thus, in such cases, where vectors c and d are *co-linear* the bilevel problem $\mathcal{B}$ reduces to the multiobjective (single-level) problem $\mathcal{M}$. Otherwise, when vectors c and d are not co-linear, problems $\mathcal{B}$ and $\mathcal{M}$ will have different solutions [28], with $\mathcal{B}$ not realizing more optimistic results than $\mathcal{M}$.

Bilevel problem formulations ($\mathcal{B}$) are meant to tradeoff conflicting objectives, just like multiobjective problems ($\mathcal{M}$). Bilevel problems find the best cx satisfying the constraints (22) and (23), while constraining y on the basis of the prior choice of x. Improvements in cx are possible until no feasible y are found, which means that here we find *one* solution.

On the other hand, with multiobjective problems, the objectives cx and $dx + fy$ are considered on the same footing. At the optimum, although changing x would affect y (through the need to maintain feasibility), an improvement in cx would lead to a corresponding degradation in the second objective $dx + fy$. The Pareto front, where the sum of the sub-objectives is minimized, represents a *set* of solutions of equal quality. The selection of one solution over the others would generally involve some degree of subjectivism.

The effective lack ambiguity of bilevel problem formulations is what makes them attractive in the context of this paper. As we are addressing the planning of a microgrid, the focus of its optimization and decisions should be at the strategic level: the choice of assets and their ratings, emission permits' management and the reliance or lack thereof on external power sources. For sure these choices are bound to have repercussions on day-to-day operations, as the lower level problem captures.

As will be seen in the following section, the solution of bilevel optimization problems is nontrivial in comparison to their multiobjective counterparts. Therefore, it is essential to ascertain that indeed the upper and lower level problems' objectives are not co-linear. It can be observed from (1) and (5) that this is indeed the case because the upper-level variable $\mathcal{R}_y^p$, which is there to capture the annual capacity charge for drawing peak power from the neighbouring community system is not present at the operational level. Therefore, the problem we are tackling here is a true bilevel problem.

2.3   Transformation to MPEC and MILP

Bilevel problems are usually difficult to solve; even the linear bilevel problem is an NP-hard problem [19]. 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 [24]. 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 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 [24], [29] 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 in the appendix, comprises replacing the lower level problem with its primal constraints (6)–(19) and its dual constraints (30)–(40). This is combined with the equality associated with the SDT (41) and the upper level problem (2), (3) to make up the transformed MPEC.

$$\min_{x \geq 0}(1) \tag{27}$$

subject to

$$\text{Constraints} \quad (2)-(3) \tag{28}$$
$$\text{Constraints} \quad (5)-(18) \tag{29}$$

dual constraints for all $t \in T$ and $y \in Y$

$$C_i^f - \lambda(y,t) - \alpha_i^{\min}(y,t) + \alpha_i^{\max}(y,t) = 0; \qquad \forall i \in D \tag{30}$$

$$C_i^f - \lambda(y,t) - \delta_i^{\min}(y,t) + \delta_i^{\max}(y,t) - \frac{\omega_i(y,t)}{\varsigma_i} = 0; \qquad \forall i \in N \tag{31}$$

$$-\lambda(y,t) - \delta_i^{\min}(y,t) + \delta_i^{\max}(y,t) = 0; \qquad \forall i \in W \tag{32}$$

$$-\lambda(y,t) - \xi_i^{\min}(y,t) + \xi_i^{\max}(y,t) - \rho_i(y,t) = 0; \qquad \forall i \in S \tag{33}$$

$$-\rho_i(y,t) - \pi_i^{\min}(y,t) + \pi_i^{\max}(y,t) = 0; \qquad \forall i \in S \tag{34}$$

$$-\lambda(y,t) - \varphi^{\min}(y,t) + \varphi^{\max}(y,t) - \sigma(y,t) = 0 \tag{35}$$

$$-\tau^{\min}(y,t) + \tau^{\max}(y,t) - \sigma(y,t) = 0 \tag{36}$$

$$-\phi(y,t) - \psi^{\min}(y,t) + \psi^{\max}(y,t) - \beta(y,t) = 0 \tag{37}$$

$$-\theta^{\min}(y,t) + \theta^{\max}(y,t) - \beta(y,t) = 0 \tag{38}$$

$$-\phi^{\min}(y,t) + \omega_i(y,t) = 0 \tag{39}$$

$$C_i^f - \phi(y,t) = 0; \qquad \forall i \in H \tag{40}$$

and the strong duality equality for all $t \in T$ and $y \in Y$

$$\sum_{i \in G}(C_i^f + C_i^z)P_i^e(y,t) + \sum_{i \in Q}(C_i^f + C_i^z)P_i^h(y,t)$$

$$= \lambda L^e(y,t) + \sum_{i \in D}(\alpha_i^{\min}(y,t)P_i^{\min} - \alpha_i^{\max}(y,t)P_i^{\max})$$

$$- \sum_{i \in \bar{B}}\delta_i^{\max}(y,t)x_i - \sum_{i \in S}(v_i\xi_i^{\min}(y,t)x_i + v_i\xi_i^{\max}(y,t)x_i)$$

$$- \sum_{i \in S}\left(\pi_{y,i}^{\max}(y,t)x_i - \rho_i(y,t)E_i(y,t-1)\right) \tag{41}$$

$$+ \sigma(y,t)E_r^e(y,t-1) - w_r^e\tau^{\max}(y,t)L^{e,\max}$$

$$- (\varphi^{\min}(y,t)k_r^e w_r^e L^{e,\max} + \varphi^{\max}(y,t)k_r^e w_r^e L^{e,\max})$$

$$+ \phi(y,t)L^h(y,t) + \beta(y,t)E_r^h(y,t-1)$$

$$- \theta^{\max}(y,t)w_r^h L^{h,\max} - (k_r^h w_r^h \psi^{\min}(y,t)L^{h,\max} + k_r^h w_r^h \psi^{\max}(y,t)L^{h,\max})$$

The non-linearities associated with the products of variables $\delta_i^{\max}(y,t)x_i$, $v_i\xi_i^{\max}(y,t)x_i$, $v_i\xi_i^{\min}(y,t)x_i$ and $\pi_i^{\max}(y,t)x_i$ in (41) of the MPEC can be linearized at the expense of more constraints and auxiliary variables, transforming the problem into an equivalent MILP problem. Equation (41) is then linearized using the techniques found in [24]. Note that all the Lagrange multipliers are positive variables here.

3   Case study

The proposed bilevel design approach is applied to a microgrid implementation of a remote mine in northern Quebec, Canada. The energy infrastructure of remote mines is characterized by unique features outlined in [30, 13] that differentiate them from most remote community microgrids.

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 5 MW diesel generator, two smaller 1.5 MW units and the rest by the community energy provider. Space heating at the mine site is provided by a gas-fired heat exchanger. The diurnal and annual daily heating and cooling profiles from [13, 31] 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 ignored. 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 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 of carbon permit one needs to buy within the auction window is used to determine the cost associated with CO_2 emission permits ($C_y^z(\Upsilon_y)$) for each generating resource i.

Table 1: Summary of input parameters.

Diesel Generator	Wind Turbine
Diesel price [32] 0.76 \$/ℓ	Capital cost [34] 2213 \$/kW
Fixed O&M [32] 15 \$/kW/yr	Fixed O&M [34] 10 \$/kW/yr
Variable O&M [32] 3 \$/MWh	
Emission rate [33] 2.64 kg/ℓ	

ESS	
Capital cost [35] 600 \$/kW	

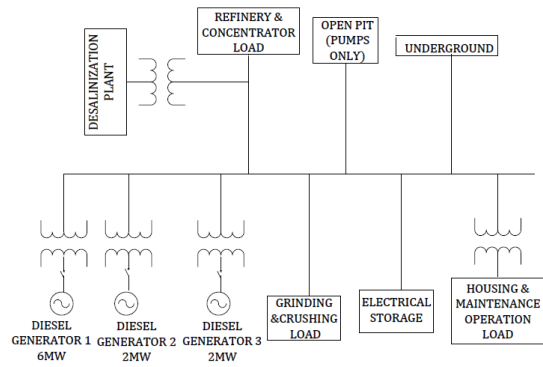| CHP	Financial parameters
Capital cost [25] 1200 \$/kW	Interest rate 3.5%
Natural gas price [25] 3.1 \$/GJ	Planning horizon 20 yrs
O&M cost [25] 0.006 \$/kWh	Carbon permits [33] 14.3 \$/ton CO_2

Figure 2: Schematic diagram of the remote mine's power system.

4   Results and discussion

4.1   Investment decisions

The above case study was evaluated using a custom-made Excel tool interfacing with the CPLEX solver of
GAMS, termed BIEX (bilevel Excel). To validate the proposed approach, the results are compared with
those of DERCAM (a commercially accepted software based on the traditional MILP) [14] and the output
is presented 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 and the MultiObjective Optimization (MOO) [10], although their optimal
configuration is comparably similar. This could be attributed to the better representation of the order of the
decision making process by the BIEX. Here, the operator has a better perspective of the designer's decision,
hence its solution lead to a lower operation cost in BIEX compared to DERCAM, where both problems
are solved concurrently. Also, the BIEX solution was compared to that of the multiobjective optimization
approach where the cost of planning is co optimized with operational cost to illustrate the difference in the
two approach. From Table 2, it can be observed that, the bilevel provided a less expensive configuration
compared to the MOO. This is due to its selection of a lesser capacity of the expensive biomass although
the biomass has a higher capacity factor. Also, the hierarchical nature of the formulation makes it possible
for the upper level problem to increase its interest (shift from the Pareto optimal) without necessary being
detrimental (to the disadvantage) to the lower level. However, the MOO formulation may have to find a
compromise (Pareto optimal) among the two objectives. Hence, its solution selects a reasonable capacity of
the expensive biomass as well as other DER as shown in Table 2. The cost presented in Table 2 (last column)
is the sum of the annualized investment cost of the design solution and annual the operational costs.

Table 2: Optimal microgrid expansion.

	Wind (kW)	CHP (kW)	ESS (kWh)	Biomass (kW)	Cost (k$)
BIEX	7458	690	3965	547	38 792
MOO	7350	579	4075	644	38 823
DERCAM	7300	600	4000	700	39 015

4.2   EMS output

The performance of the EMS is presented in Figure 5 and Figure 7, while Figure 4 shows the hourly generation
profile of the generating units in the base case. Figures 5 and 7 also show the electrical and thermal output
of DERs set by the EMS on a typical day. It could be observed from Figure 4 that the mine often utilizes all
its three generators in the base case while keeping the third diesel unit (Diesel III) constant at its maximum
operating point and buying last resort power from the remote community energy provider.

However, with the implementation of the EMS in Case III, the two smaller generators (*i.e.*, Diesel I and Diesel II) and power from the remote community are not utilized. However, with the implementation of the EMS, the two smaller generators (*i.e.*, Diesel I and Diesel II) Considering the difference in efficiency when the generators operate at lower loads(below 50%) and the capacity of the generators, microgrid implementation results 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 as well as power purchased from the remote community 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 the total 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. Also the performance of the EMS in the case where the MOO approach is considered is shown in Figure 6.
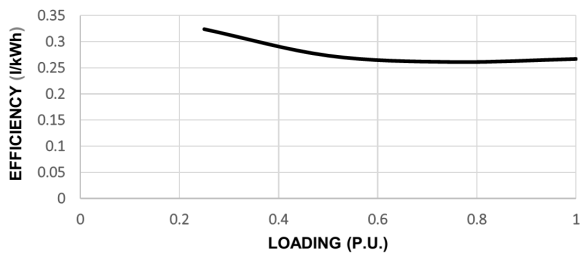

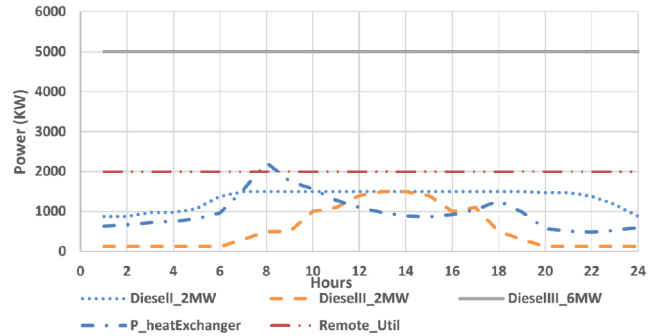Figure 3: Generation efficiency of 1.5 MW Diesel I and II.

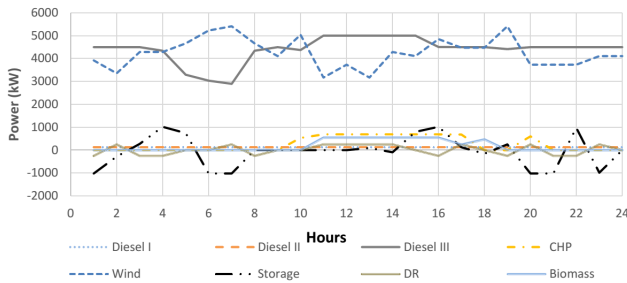Figure 4: Generating units operating point in a typical day.

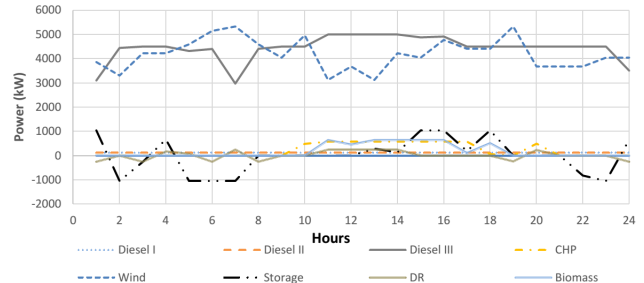Figure 5: Electrical output of DERs in a typical day for BIEX.

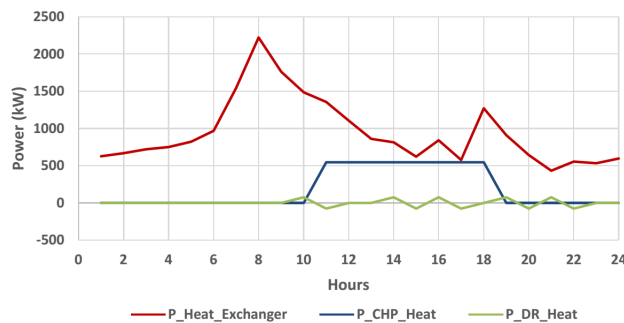Figure 6: Electrical output of DERs in a typical day for MOO.

Figure 7: Thermal Output of DERs in a typical Day.

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 (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 bilevel planning strategy was subjected to cost benefit analysis. Results obtained show significant savings in energy costs for all three planning scenarios or cases. Nevertheless, case III happens to yield the most benefit to all participating stakeholders. Table 3 outlines the outcome of the economic analysis for all three scenario. It illustrates the benefit to cost ratio or PVR for the corresponding stakeholders (the mine's management in this case). 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 savings. The low PVR in the third scenario is due to the high penetration level of DER's which further translates into a higher capital investment cost.

Table 3: Per unit costs and benefits.

Costs	Base case	Case I	Case II	Case III
Emissions	0.175	0.080	0.088	0.080
Fuel	0.611	0.360	0.590	0.360
Power	0.214	0.000	0.000	0.000
Investment	0.000	0.038	0.045	0.269
Total	1.000	0.784	0.723	0.708
Savings	–	21.61%	27.7%	29.22%
PVR	–	–	–	1.08

4.3.1   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.

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 sequentially 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 return 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.

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