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Optimal planning of microgrid power and operating reserve capacity☆

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HIGHLIGHTS

- A bi-level model for a microgrid power and reserve capacity planning is developed.
- The model is cast within the context of a distribution system operator (DSO).
- The DSO and microgrid relationship is established in a structural/economical manner.
- Results obtained show bi-level optimization decreases overall operating cost.

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ABSTRACT

This paper proposes a bi–level formulation for a coupled microgrid power and reserve capacity planning problem, cast within the jurisdiction of a distribution system operator(DSO). The upper level problem of the proposed bi–level model represents a microgrid planner whose goal is to minimize its planning and operational cost, while the lower level problem represents a DSO whose primary duty is to ensure reliable power supply. The microgrid planner, pursues its interest by co–optimizing the design configuration and power output of individual distributed energy resources (DERs), while the DSO maximizes the capacity of flexible reserve resources. The proposed model is recast as a mathematical program with equilibrium constraints (MPEC) wherein the decision variables of the two problems are independently controlled. Application of the proposed approach to the energy infrastructure of a Canadian utility network is discussed. Results obtained through its application are compared to an alternative multi–objective planning model and the improved benefits are assigned to the corresponding stakeholders.

1. Introduction

The electric power industry has undergone notable changes in recent years. The traditional central grid is experiencing a shift toward distributed generation, increased penetration of renewable energy and utilization of demand response (DR) resources [1]. The gradual transformation of the grid and penetration of intermittent energy resources challenge utilities' ability to maintain reliable and economical system operations. Many solutions have been suggested, and among them is microgrid technology, which comes with the promise of integrating renewable resources and improving local system reliability and efficiency [2,3]. Microgrids can also provide valuable grid services, e.g. ancillary services and demand-side management [4]; however, these resources can only contribute significantly to displacing capacity and flexibility of the main grid through aggregation and effective power system management and control. Another important issue is that, the transmission system operator (TSO) has no visibility and control of microgrid resources, and traditionally, the distribution system operator (DSO) also has very limited control over these assets. Further, the small scale and large numbers of diverse assets would push the limits of current control technology. Taking full advantage of services and benefits provided by microgrids will challenge the megagrid; consequently, the operational and planning arrangements within power systems must be revised to support a new distribution system operation paradigm that enables the provision of grid services by microgrids.

To this end, new roles have been proposed for a future DSO within a new DSO construct/paradigm [1,5–7] structured to accommodate microgrids and other prosumers. The DSO is responsible for local ancillary

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Nomenclature

Indices and sets

- i index for all energy resources
- r index for reserve
- t index for hour
- y index for years of project lifetime
- z index for demand response (DR)
- A set of existing resources i in the network
- B set of indices for new distributed energy resources (DERs)
- $\overline{B}$ set of indices of new DERs except storage
- D set of indices of diesel generating units
- G set of dispatchable generating units
- S set of electrical energy storage (ESS) devices
- T set of indices of time t within a year
- W set of indices of wind power generating units
- Y set of indices of years in the project lifetime J

Parameters

- k_z^e electrical DR energy to power ratio
- k_z^h thermal DR energy to power ratio
- ν_i energy to power ratio of storage resource i
- w_z^e percentage of electrical load available for DR
- w_z^h percentage of thermal load available for DR
- C^b budget constraint for resource i
- C_i^c cost per unit capacity of resource i
- C_i^f fuel cost of resource i
- C_u unit cost of purchased energy from utility i
- C_i^r cost of reserved capacity of resource i
- $C_y^{\wp}$ cost of carbon allowance per $kgCO_2$ in year y
- C_i^m maintenance cost for resource i
- $X_i^{\max}$ maximum power capacity of a new resource i
- $P_i^{\max}$ maximum power output of an existing resource i
- $P_i^{\min}$ minimum power output of an existing resource i
- $L^e(y,t)$ electrical load at time t in year y
- $L_y^h(y,t)$ thermal load at time t in year y
- $L_y^{e,\max}$ peak electrical load
- $L_y^{h,\max}$ peak thermal load
- η_i storage charging and discharging efficiency
- ς_i electric to heat ratio of CHP unit

Microgrid planner level variables

- $E_i^e(y,t)$ electrical energy level of ESS i at time t in year y
- $P_i^e(y,t)$ 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
- $P_z^e(y,t)$ electrical output from DR resource z at time t in year y
- $P_z^h(y,t)$ thermal output from DR resource z at time t in year y
- x_i capacity of DER assets i

DSO Level variables

- R_i reserve capacity provided by resource i
- $P_i^r(y,k,t)$ post-contingency power output of resource i following contingency event k at time t in year y.

service (AS) markets, acting as an interface between the TSO and demand-side or distribution-level market players. Also, operational and planning information or orders are exchanged and coordinated between the DSO and the TSO to ensure the successful operation of local AS markets, while, the DSO may request reserve provision from local retail market agents, including microgrids. A microgrid planner working within this new DSO paradigm faces a dilemma between satisfying the DSO reserve capacity requirement, and pursuing its own interest of minimizing the design and operational cost of its microgrid. To assist microgrid plannners make such difficult choices, researchers have proposed various operational strategies and models. Among these is the market-based mechanism developed by the authors in [8], which enables a *smart microgrid operator* to offer regulation service while meeting the associated obligation of fast response to commands issued by a wholesale market independent system operator (ISO). Furthermore, an energy management tool for next-generation photovoltaic (PV) installations, including storage units, is proposed in [9] to provide flexibility to DSOs. Several microgrid planning models have been proposed in [10–18] to minimize costs and improve reliability, as well as deliver other microgrid benefits. Particularly, a particle swarm optimization approach is proposed in [13] to co-optimize DERs for community microgrids while meeting U.S. Department of Energy (DOE) requirements and state renewable energy mandates.

A reflection of the relationship between the DSO and microgrids at their planning/design stage is needed for an effective operation of microgrids within the new DSO paradigm. Bi–level programming models are well suited to characterize such complex relationships. These models are characterized by two decision makers at different hierarchical levels, each independently controlling only a limited set of decision variables, and each may have single or multiple objectives. The lower level executes its policies after the upper one, considering its decisions; while the higher level optimizes its objective in anticipation of the reactions of the lower level. Further reading on bi-level programming can be found in [19–23]. Within the context of microgrid applications, bi-level models have been proposed by authors in [24–26] to minimize coupled design and operational costs. In [26], the authors propose a microgrid planning and operational problem, nested in the form of a generalized double-shell framework. The outer shell minimizes the microgrid's capital cost, which is aligned with the inner shell's objective of minimizing the operational cost. The aligned objectives of these formulations may not merit a bi-level approach since other mathematical programming models such as multistage or multi-objective planning models are adequate.

This paper proposes a non co–linear bi-level power and reserve planning formulation for the DSO and microgrid planning problems, wherein, a DSO whose duty is to ensure reliable power supply may request reserve capacity from a microgrid planner whose interest is to minimize its planning and operational cost. The proposed formulation can be seen as a classical example of a Stakelberg game where the upper level or leader's problem characterizes the actions of the microgrid planner, and the lower level or follower's problem represents that of the DSO. The proposed model also seeks to establish a better representation of the potentially conflicting relationship between the microgrid planner and a DSO within the new DSO construct.

The rest of the paper is structured as follows: Section 2 provides an overview of the new DSO construct while Section 3 outlines the proposed bi–level formulation and its transformation into a mixed integer linear programming problem (MILP). Section 4 discusses a case study implementation for a Canadian utility network. Section 5 discusses the results obtained and Section 6 provides brief concluding remarks.

2. Overview of the new DSO construct

Given that the likely future power grid will have numerous distribution-level market agents and a matrix of interconnected microgrids, a new DSO construct is required to define new roles for a future DSO as well as clarify the extent to which a DSO can actively contribute to macro system operation. The new construct has the DSO accept responsibility for distribution level balancing, supply and demand variations. It will also link wholesale and retail market agents while maintaining the traditional role as a custodian for distribution system reliability. The paradigm shift is propelled by New York Public Service Commission, which in late April 2014 opened related proceedings ("Reforming the Energy Vision of REV") [27] to rethink the central–-station utility paradigm, and redefine the local distribution utility as a trading platform for various products and services, provided by diverse market players [1,5–7]. New business models for extended central dispatch, local dispatch by the DSO and scheduling at the HV/MV interface that can be implemented together are being discussed. The evolving structure and organization of power systems can capture the full benefits of microgrids [6]. Business models will provide opportunities for both TSOs and DSOs to efficiently use microgrid services. Local dispatch in which the DSO could procure services to satisfy its own needs and the TSO's, is the main interest of this paper. Here, the TSO will not act on any individual DERs connected to the distribution grid; however, orders from the TSO can be executed by the DSO. It is within the context of the local DSO model and the paradigm shift towards a new DSO construct, that the proposed microgrid planning model outlined in this paper is developed.

3. Methodology

3.1. Bilevel model outline

As mentioned in the introduction, the structure of the bi-level formulation as illustrated in Fig. 1 fits into the narrative of the new DSO construct described in the previous section. Here, the actions of the microgrid planner are represented by the upper level problem while the DSO's decisions are represented by the lower level problem. The decision-making process is sequential with the microgrid planner having the first choice of design configuration (capacity of DERs, $x_i\ ;\forall\ i\in B$) and dispatch set points ($P_i\ ;\forall\ i\in G$) that minimizes its total planning and operational cost. In view of the planner's decision, the DSO, determines reserve capacities of DERs that the microgrid will provide. The available operating space of the lower level's problem is constrained by the decision of the upper level. The microgrid planner upon observing the reaction of the DSO may alter his selection. This process is repeated until an equilibrium is found where neither level has an incentive to change its selection.

3.1.1. Planning and design – upper level problem

The upper level objective function 1, co–optimizes the annualized investment cost of new DERs (first term), annual operational cost of the microgrid (second term) over the planning horizon and the cost of carbon permit purchases (third term). The variable x_i and P_i denote the capacities of DER options to be installed and the operation set points of the dispatchable resources respectively; these constitute the solution to the upper level problem. The total planning and operational cost is converted into its present value by the factor γ, with ϱ_y being the capital recovery factor.[1]

$$\min_{x,P\geqslant 0} \gamma \sum_{y\in Y} \{\varrho_y \sum_{i\in B} C_i^c x_i + \sum_{t\in T} C_y(P) + \sum_{t\in T} C_y^{\wp}\wp\} \tag{1}$$

where $C_y^{\wp}\wp_y$ is the cost of carbon permits $\wp_y$ in year y and $C_y(P)$ is defined by:

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

$$\rho(0)\sum_{t\in T}\{\sum_{i\in G} C_i^f P_i^e(y,t) + C_u P_u^e(y,t) + \sum_{i\in Q} C_i^f P_i^h(y,t)\} + \sum_{k\in K}\sum_{t\in T}\rho(k)\{\sum_{i\in G} C_i^f P_i^e(y,k,t) + C_u P_u^e(y,k,t) + \sum_{i\in Q} C_i^f P_i^h(y,k,t)\} \tag{2}$$

The first component of the operational cost $C_y(P)$ is divided into two parts: the first part covers the generation cost during normal operation of the power system (and is multiplied by the probability of non-occurrence of any pre-selected contingency event $\rho(0)$) while the second part covers the cost during contingency $k\in K$ in the microgrid and multiplied by the probability of its occurrence $\rho(k)$. The quantity $\rho(k)$ is calculated from expected mean time to failure data (taken to be constant over the scheduling horizon [28]) as detailed in [28].

The upper level objective is constrained by a budget allocation for investment (3) and allowable carbon permits purchased (4):

$$\sum_{i\in B} C_i^c x_i \leqslant C^b \tag{3}$$

$$\sum_{i\in D}\sum_{t\in T}\zeta_i P_i^e(y,t) + \sum_{i\in Q}\sum_{t\in T}\zeta_i P_i^h(y,t) \leqslant \wp \tag{4}$$

where ζ_i is the emission coefficient of resource i.

The upper level problem is further constrained by hourly generation and load balance, (5) and (6), while both thermal and electrical loads are considered. The electrical power balance is given by

$$\sum_{i\in E} P_i^e(y,t) = L^e(y,t) \tag{5}$$

while the thermal power balance requires

$$\sum_{i\in H} P_i^h(y,t) = L^h(y,t) \tag{6}$$

The hourly dispatch problem is further constrained by maximum and minimum limits of the dispatchable generating resources including CHP, (7) and (8) given below:

$$P_i^{\min} \leqslant P_i^e(y,t) \leqslant P_i^{\max} - R_i \tag{7}$$

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

$$0 \leqslant P_i^e(y,t) \leqslant x_i - R_i \tag{8}$$

for all $i\in B, t\in T$ and $y\in Y$. The heat output from the CHP is given by (9)

$$P_i^h(y,t) = \frac{P_i^e(y,t)}{\varsigma_i} \tag{9}$$

for all $i\in N, t\in T$ and $y\in Y$.

The operation of the electrical storage system (ESS) in the microgrid

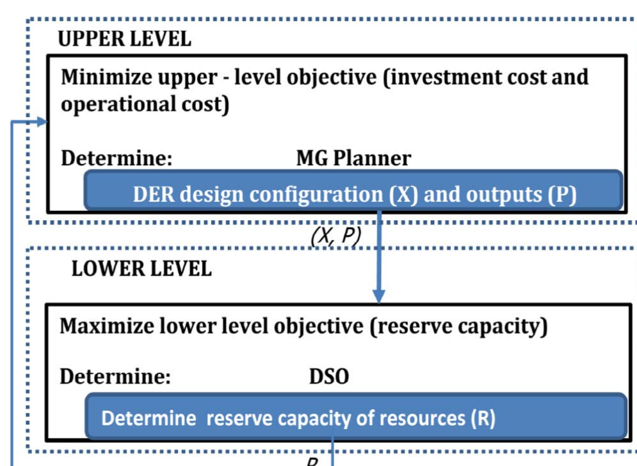

Fig. 1. Schematic diagram of the bilevel planning and reserve capacity model.

is also constrained by (10)–(12), for all $i \in S, t \in T$ and $y \in Y$. 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.

$$E_i(y,t) = E_i(y,t-1) + \eta P_i(y,t)\Delta t \tag{10}$$

$$0 \leqslant E_i(y,t) \leqslant v_i(x_i - R_i) \tag{11}$$

$$-(x_i - R_i) \leqslant P_i(y,t) \leqslant x_i - R_i \tag{12}$$

Subsequently, the dispatch problem is also subject to limits on energy available for electrical DR, (13) and (14). Eq. (15) outlines the constraint on the hourly electric energy available for demand response. Similar to the ESS, k_z^e is dependent on the DR technology/strategy used. The electric-side DR has to satisfy

$$E_z^e(y,t) = E_z^e(y,t-1) + P_z^e(y,t)\Delta t \tag{13}$$

$$0 \leqslant E_z^e(y,t) \leqslant w_z^e L^{e,\max} - R_i \tag{14}$$

$$-k_z^e(w_z^e L^{\max} - R_i) \leqslant P_z^e(y,t) \leqslant k_z^e(w_z^e L^{\max} - R_i) \tag{15}$$

for all $i \in z, t \in T$ and $y \in Y$.

3.1.2. DSO – lower level problem

The lower level problem represents the DSO's objective of maximizing reserve capacity provided by the microgrid to support the power system's operation. The objective function as outlined in (16) minimizes outage cost by minimizing non–delivered energy for a given period t during a contingency k (first term), as well as minimize the cost of reserve capacity (last term). It is worth noting that C_i^r is determined based on a long term contract and assumed to be given in "$"/$kW$–per year for purposes of this work.

$$R_i \in \underset{R_i, P_i^r}{\operatorname{argmin}} \sum_{y \in Y} \sum_{i \in G} \{ \sum_{t \in T} \sum_{k \in K} \Upsilon_i (L^e(y,k,t) - \sum_{t \in T} P_i^r(y,k,t)) + C_i^r R_i \} \tag{16}$$

The lower level's objective is constrained by DER capacities x_i, $\forall\, i \in G$ and a limit on the available reserve energy according to (17) and (18) respectively:

$$0 \leqslant R_i \leqslant x_i; \tau_i^{\min}, \tau_i^{\max} \tag{17}$$

$$0 \leqslant P_i^r(y,k,t) \leqslant R_i; \varphi_i^{\min}(y,k,t), \varphi_i^{\max}(y,k,t) \tag{18}$$

here, x_i for existing assets are known and equal to P_i^{max}, $\forall\, i \in D$ while x_i for new assets $i \in G \subset B$ are part of the decision variables passed by the upper level problem.

The lower level problem, must also satisfy post contingency power balance (19):

$$\sum_{i \in E} P_i^e(y,k,t) + P_i^r(y,k,t) \leqslant L^e(y,k,t); \lambda(y,k,t) \tag{19}$$

where $\lambda(y,k,t)$ and $\phi(y,k,t)$ are the Lagrange multipliers associated with those constraints.[2] While the microgrid provides reserve capacity during its normal operation, there should also be enough capacity to support its load during an event $k \in K$.

3.2. Transformation to MPEC and MILP

The proposed bilevel problem is an NP-hard problem [19] and difficult to solve. Thus, it 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 [19]. Obviously, 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 for 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 [19,20] 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, the primal-dual approach is applied in this work. The transformation, as outlined below, comprises replacing the lower level problem with its primal constraints (17)–(19) and its dual constraints (23) and (24). This is combined with the equality associated with the SDT (25) and the upper level problem (3), (16) to make up the transformed MPEC.

$$\min_{x \geqslant 0}(1) \tag{20}$$

subject to

$$\text{Constraints}(3)\text{–}(15) \tag{21}$$

$$\text{Constraints}(17)\text{–}(19) \tag{22}$$

dual constraints

$$C_i^r - \tau_i^{\min} + \tau_i^{\max} + \varphi_i^{\min}(y,k,t) - \varphi_i^{\max}(y,k,t) = 0\ \forall\, i \in G \tag{23}$$

$$\Upsilon_i - \lambda(y,k,t) - \varphi_i^{\min}(y,k,t) + \varphi_i^{\max}(y,k,t) = 0\ \forall\, i \in G \tag{24}$$

and the strong duality equality

$$(\Upsilon_i(L^e(y,k,t) - \sum_{t \in T} P_i^r(y,k,t)) + C_i^r R_i) = \lambda(y,k,t) L^e(y,k,t) + \sum_{i \in G} \tau_i^{\max} x_i \tag{25}$$

The non-linearities associated with the products of the upper variable x_i and Lagrange variables in (25) of the MPEC can be linearized at the expense of more constraints and auxiliary variables, transforming the problem into an equivalent MILP problem [19]. Thus, Eq. (25) is linearized using the techniques found in [19,29,30] and outlined in the appendix. Note that all the Lagrange multipliers are positive variables here.

4. Case study

The proposed bi–level microgrid planning approach is applied to a microgrid implementation within a distribution network in the western part of Canada. The local electric utility, supplies energy to potential customers of the microgrid at a rate of 12.23 ¢/kW h.[3] There is also a customer charge of 23 ¢/day and an average demand charge of 10.42 "$"/kW per month. The average yearly demand of customers is 1 MW with a peak demand of 1.2 MW and an annual load growth of 2%. Available reliability records indicate that the grid has three failures per anum on the average. The cost of non–delivered energy (NDE) is taken as 25 "$"/kW h [31] while heat is provided by the local gas utility. The charges for reserve capacity is taken as 1.1 "$"/kW [32]. Here, the cost of reserve capacity is assumed to be the same for all reserve resources. Prior to microgrid investment, there was a 420 kW diesel generator installed to support critical/sensitive load. The existing local distribution system infrastructure with no microgrid functionality is considered to be the base case. Here, the existing assets support or meet some portion of their local load during normal operation and maintain supply

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

[3] All ¢ and "$" are in canadian dollars (CAD)

to sensitive loads during an emergency. DER considered for the microgrid implementation include wind turbines, combined heat and power (CHP), ESS, DR and an energy management system. ESS technology considered is a new generation compressed air energy storage system with a ratio of energy storage capacity to power capacity v_i of four hours. It is also assumed that 10% of the load is available for DR operation. A hypothetical layout of the microgrid connected to the grid is provided in Fig. 2. Economic parameters of the existing and new DERs as well as other required data are provided in Tables 1 and 3. The probability $\rho(k)$ of an event k due to a failure of a resource i in time $t \in T$ of year $y \in Y$ is given in Table 2 based on parameters obtained from [33,34]. Four 24 h daily load scenarios are used in modeling the load for the system with each daily profile representing a season. They are aggregated by a factor based on the number of days in a season. Consequently the optimization model runs for a 24 h schedule window for all the seasons in the year. Here, we consider only single failures and assumed that, when an event k occurs, it may last for rest of the day. Assets depreciation based on capital cost allowance (CCA) is applied to the energy infrastructure in this work. The cost associated with CO_2 emission ($C_i^{\wp}$) is taken to be 14.32 "$"/t$CO_2$, the clearing price of carbon permits in an auction window on the carbon market.

5. Results and discussion

5.1. Planning decisions

The proposed planning model is evaluated using a custom-made *Excel–VBA* tool interfaced with the CPLEX solver under GAMS, termed BIEX (BI-level EXcel). Here annual optimization of the proposed model is run for the entire planning horizon. Results obtained based on the proposed approach are compared with those of a more traditional multi–objective optimization (MOO) [12] where the DSO and the microgrid are considered concurrently. The results of the planning exercise are shown in Table 4, k"$" has no relation contigency k in the formulation. Both algorithms were provided with the same input data and parameters to make the comparison valid. Both cases are also compared with the base case (Base Case) which has no microgrid energy infrastructure and the results shown in Table 4. From Table 4, it could be observed that, the implementation of the proposed bi–level model and the MOO model yielded lower annualized costs of energy when compared to the base case. Nonetheless, the optimal configuration of the proposed model resulted in a lower cost of operation when compared to that of the MOO algorithm. This can be attributed to the fact that, in the bi–level model, either of the levels (microgrid planner or the DSO) could increase its interest without necessarily compromising the interest of the other, where as in the multi–objective case, an increase in the objective of one of the players may require a

Table 1
Summary of input parameters of existing assets.

Diesel Generator	
Fuel cost [35]	0.76 ("$"/l.)
Fixed O&M [35]	15 ("$"/kW-yr)
Variable O&M [35]	3 ("$"/MW h)
Emission rate [36]	2.64 (kg/l.)

Table 2
Reliability data for Microgrid DERs.

DERs (i)	$\rho(k)$
Wind turbine	2.80×10^{-5}
CHP	2×10^{-5}
ESS	1.857×10^{-5}
Diesel generator	3.598×10^{-3}

Table 3
Summary of input parameters.

ESS	Wind Turbine
Capital cost [37] 600 ("$"/kW h)	Capital cost [38] 2213 ("$"/kW) Fixed O&M [38] 10 ("$"/kW–yr)
CHP	Financial Parameters
Capital cost [39] 1200 ("$"/kW) Natural gas cost [39] 3.1 ("$"/GJ) O&M cost [39] 0.006 ("$"/kW h)	Interest rate 3.5% Planning horizon 20 yrs Escalation rate 3%

Table 4
Optimal microgrid configuration.

	Diesel (kW)	Wind (kW)	CHP (kW)	ESS (kW h)	Cost (k$/year)
Base Case	420	0	0	0	1003
BIEX	420	3000	1546	750	495
MOO	420	3000	870	750	596

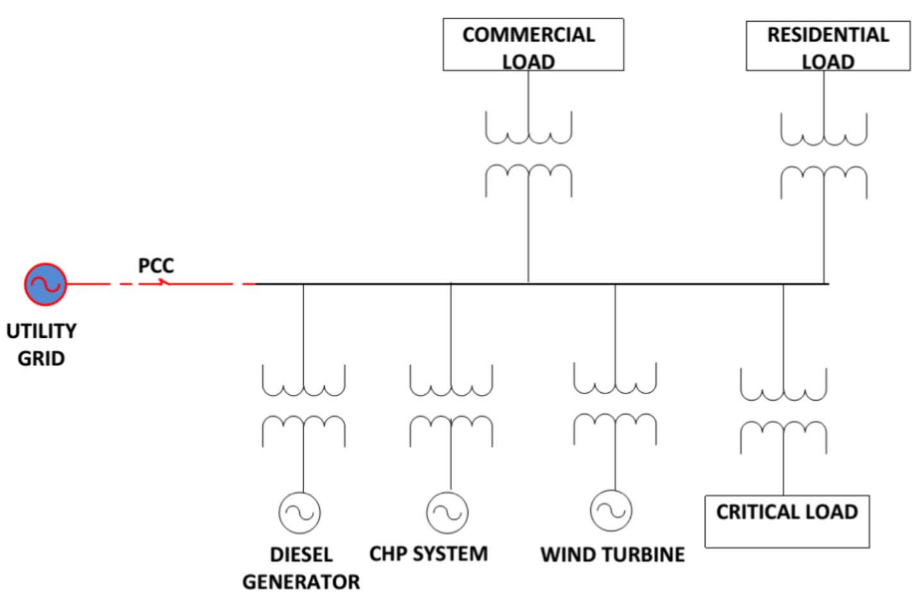

Fig. 2. Single line diagram of a generalized microgrid.

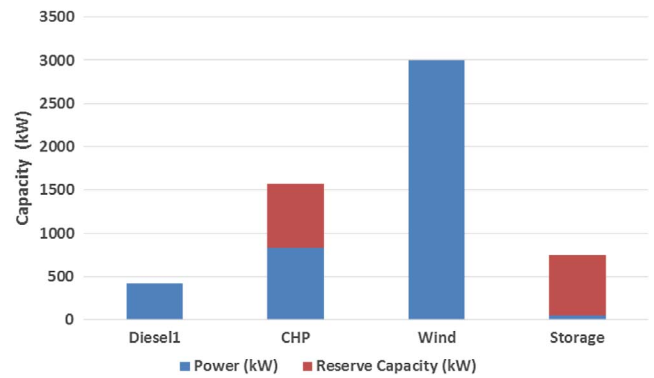

Fig. 3. Capacity of resources available for reserve and normal operation in the microgrid (Bilevel case).

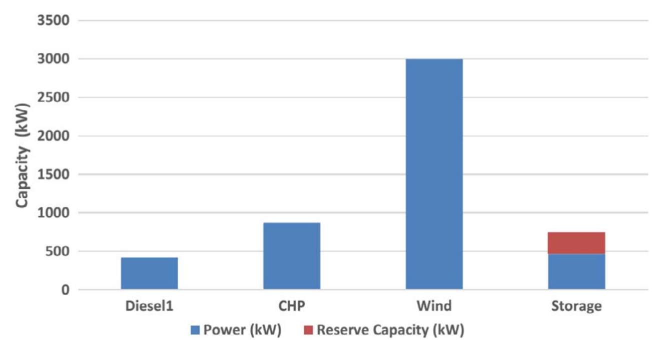

Fig. 4. Capacity of resources available for reserve and normal operation in the microgrid (MOO Case).

Table 5
Per unit costs and benefit allocation.

Stakeholders	Costs	Base case	Microgrid case
Microgrid Owner	Energy	0.89	0.393
	NDE	0.11	0
	Total	1.000	0.393
Savings			0.607
DSO	NDE	0.11	0.000
	Network Reinforcement (Investment deferral)	0.06	0.000
	Total	0.16	0.000
Savings			0.160

Table 6
Comparison of optimal microgrid configuration for the ESS case and the DR case.

	Diesel	Wind (kW)	CHP (kW)	ESS (kW h)	Cost (k$/year)
ESS	420	3000	1578	750	536
DR	420	3000	2510	0	703

compromise from the other objectives, i.e. an increase in the interest of the microgrid planner to minimize cost may require some compromise on reliability from the DSO.

Furthermore, it can be seen from Figs. 3 and 4 that, in both the proposed bi–level model and the MOO model, the capacities of resources allocated for reserve services are different. In the case of the proposed bi–level model, about 46.6% of its CHP design capacity and 93.5% of the design capacity of ESS are allocated for reserve provision. However, with the MOO implementation, only 37.1% of the design capacity of ESS is available for reserve provision while the other resources are used for normal operation of the microgrid.

5.2. Allocation of benefits to stakeholders

Benefits realized from the implementation of the proposed microgrid configuration approach are assigned to corresponding stakeholders and shown in Table 5. Here, it is assumed that the microgrid is customer owned, hence, the main stakeholders considered are the microgrid owner/customer and the DSO. Consequently, three main benefits were realized: reduced energy cost, improvement in reliability and investment deferral. Prior to the implementation of the proposed microgrid, the non-transformed microgrid system was a net importer of energy from the distribution system it is connected to. However, with the modification of the network into a microgrid, enough capacities of DERs were available to support the microgrid load while surplus energy is supplied to the distribution system. Excess energy supplied to the distribution system translates into additional revenue to the microgrid owner and thus reduces cost of energy for the microgrid owner/customer. Also, incorporation of reserve planning at the design stage of the proposed model ensures that there is adequate capacity of resources to maintain reliable power supply for all microgrid customer loads, unlike the base case, where only critical loads were supported in the event of a contingency. Additional investment needed to enforce the local distribution system to support growth in peak load (annual growth of 2%) is differed because of additional capacity provided by the installed DERs in the microgrid. It could also be observed from Table 5 that, reduced energy cost is assigned to the microgrid owner and customers while investment deferral is assigned to the DSO. Also, reliability improvement or reduced NDE seems to benefit both the microgrid owner and DSO. It is also important to note that emission reduction is not considered in this analysis. This is due to the fact that, power supply to customers of the existing network (base case) prior to its transformation into a microgrid was from a hydro source. Thus the argument for emission reduction cannot be sustained.

5.3. ESS versus demand response

Attempts were made in this work to analyze the impact of the net benefit of each non–generating flexible resources namely DR or ESS on the planning configuration of the proposed model. Here we consider the case where a microgrid planner has to make a choice between an ESS and a DR technology and the resulting configuration is presented in Table 6. It could be observed from the table that, the optimal configuration of both cases differs from the previous cases where both technologies were available for selection. In the ESS *only* case, the configuration and resources available for reserve provision as shown in Fig. 5 is similar to the optimal configuration in the case with all technologies available, however, the same cannot be said about the DR *only* case shown in Fig. 6. Also the annualized cost of the ESS only case is lower than that of the DR *only* case where no ESS is considered. Thus, one may opt for the ESS only technology mix in the microgrid design and experience comparatively similar benefit as installing both ESS and DR technology. Nonetheless, it is worth noting that, the capacity of energy available for DR operation is far less than the capacity of ESS installed.

6. Conclusion

A bilevel optimization model for a coupled microgrid - DSO planning problem has been developed and implemented in this work. The coupled problem is cast as a hierarchical decision making model where the microgrid planner determines the design capacity of DERs and their outputs, while the DSO determines the reserve capacities of these resources based on the microgrid planner's decision. The proposed model is recast as an MPEC and transformed into an MILP based on the strong duality theorem. Implementation of the proposed to a Canadian utility network is presented in this work and the results are compared with an alternative MOO. A comparison of the results of the two optimization tools (traditional MOO and the proposed bi–level approach) shows

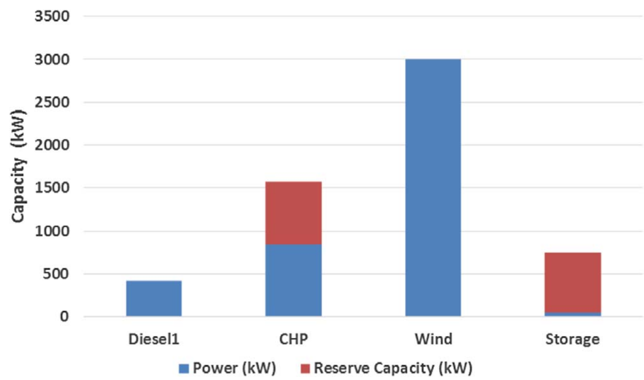

Fig. 5. Capacity of resources available for reserve and normal operation in the microgrid (Bilevel Demand response only case).

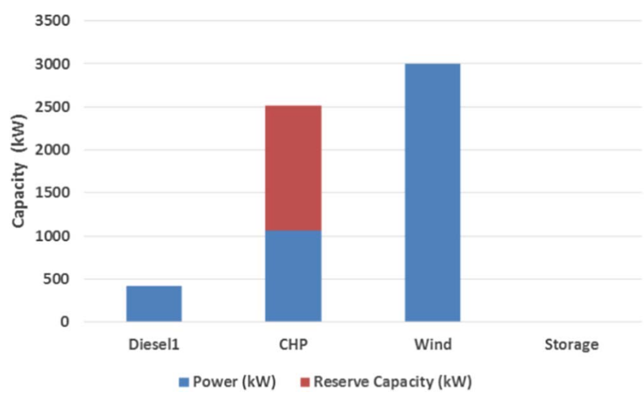

Fig. 6. Capacity of resources available for reserve and normal operation in the microgrid (Bilevel ESS only with no DR case).

lower total energy cost in the proposed approach. The work also establishes the relationship between the DSO and the microgrid in both a structural and an economical manner. Further analysis were undertaken to determine the impact of demand response and electrical energy storage. The analysis is to help policy makers draft informed policy decisions aimed at supporting either of these technologies. Likewise, the analysis can help a microgrid stakeholder or planner whose interest is to implement either of these technologies.

Appendix A. Linearization

The nonlinear expression $\tau_i^{\max} x_i$ in (25) is linearized by introducing an auxiliary variable $q_i = \tau_i^{\max} x_i$ and a big value $\mathscr{A}$ as the upper limit of the dual variable τ_i. Here, the term $\tau_i^{\max} x_i$ is replaced by q_i and constraints (26)–(30) based on McCormick's relaxation [19,29,30]:

$$q_i \geqslant X_i^{\max}\tau_i^{\max} + \mathscr{A}x_i - \mathscr{A}X_i^{\max} \tag{26}$$

$$q_i \leqslant X_i^{\max}\tau_i^{\max} \tag{27}$$

$$q_i \leqslant \mathscr{A}x_i \tag{28}$$

$$0 \leqslant x_i \leqslant X_i^{\max} \tag{29}$$

$$0 \leqslant \tau_i^{\max} \leqslant \mathscr{A} \tag{30}$$

Note however, that constraint (26)–(28) are the additional constraints introduced.

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