Optimal Nanogrid Planning at Building Level

S. Moradi, V. Vahidinasab, G. Zizzo

Abstract

This paper presents a planning framework for active buildings as an Energy Nano-Grid (ENG) determining the optimal size and the generation mix of energy resources, the ENG type which is be able to be either AC or DC, as well as the optimal energy management (EM). Due to the increasing penetration of the battery energy storage devices, Electrical Vehicles (EVs) and also DC loads in the consumer-side, DC ENGs would be potentially more useful than AC ENGs by reducing the use of converters, facilitating the connection of various types of DERs and loads to the common bus with simplified interfaces, and mitigating losses associated with the AC/DC energy conversion. Therefore, selection of the ENG type is an economic issue, where the planning objective includes the investment, operation, and maintenance costs of energy resources, investment cost of battery energy storage (BES) and converters, cost/income of energy purchase/sell from/to the upstream network or neighbor ENGs. So, an optimal power flow (OPF) could also be reached in result of the proposed program. Using some numerical case studies associated with three ENGs, the proposed planning model is analyzed to demonstrate the applicability, effectiveness, and control.

Index Terms—Active residential building, AC nanogrid, DC nanogrid, planning, PV power system, wind power system, battery energy storage (BES), electrical vehicle (EV), energy management.

I. INTRODUCTION

A. Aims and Scopes

Thanks to the advent of new technologies such as renewable-based micro energy sources, energy storage systems as well as small-scale co-generations into the building sector, there is a pressing need for the whole systems approach to the planning of building energy systems. The whole systems approach involves evaluating the various components of the system and rethinking the relationships between each of them and even redesigning the system. Confidently, such a complex energy system, faces conflicting challenges of security, equity and sustainability, which are often referred to as the energy trilemma (see Fig. 1). [1-3].

Nowadays, buildings are responsible for about 40$\%$ of carbon emissions. In the UK, they consume about 40% of all energy produced. Any solution to the energy crisis will have to address the issue of energy in buildings [4]. Recent developments in smart building technologies, clearly show that the buildings of the future have the potential to be active and energy self-sufficient entities that when connected with other active buildings or upstream grid in a network, could have the ability to trade energy [5-6].

To enable energy resilient communities that are powered by the sun and wind and are be able to share energy with neighbors and transport systems, this paper proposes a comprehensive techno-economic framework for the optimal planning and demand-side management of the buildings as

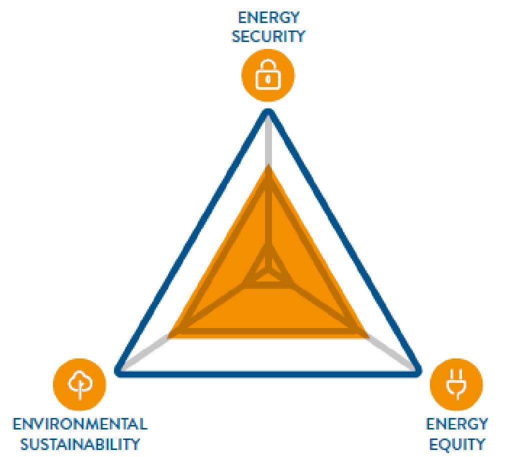


Fig. 1. The energy trilemma triangle [1].

an Energy Nano-Grids (ENG) that can actively participate in the two-vector energy and transport system.

B. Research Challenge

The main point of the challenge here is to decide on the optimal type of the building-based nanogrid, either AC or DC, based on the system specifications such as the ratio of DC load at ENG, the capacity of installed Battery Energy Storage devices (BESs), and maximum energy that electrical vehicles (EVs) can deliver to the ENG or upstream network, accordingly determine the optimal mixture of solar and wind power (S and WP) generators and BESs as generation portfolio.

C. Literature Survey

Table I presents a taxonomy of existing approaches and reviews the previous researches. In [7], a networked nanogrid and a battery swapping station (BSS) are considered to be programmed in which nanogrids can share their surplus energy or store it at BSS serving energy for electrical vehicles at pick hours. One of the challenging issues in this study is that energy must be transmitted to BSS by the delivery system which increases the operation and investment costs. Ref. [8] represents a planning model for microgrids connected to the upstream grid to measure the optimal size, generation mix of DERs and the type of microgrids. This paper evaluates how various factors like the rate of dc and critical load and the efficiency of converters determine whether microgrids should be DC or AC.

Ref. [9] developed the model in [8] and shows that, in some cases, hybrid (AC/DC) microgrids can be more economical than other types by reducing the number of converters. In ref. [10], power and voltage control of a hybrid building nanogrid with two AC and DC buses are performed in both grid-connected and off-grid states. [11] represents residential units as energy hubs, so, in addition to electrical components, structural optimal sizing of combined heat and power (CHP) unit, gas boiler and heat storage systems should be measured. Ref. [12] illustrates some DC residential nanogrids connected to each other and to the main grid. Importing and exporting of electricity is controlled by an online cyber-physical approach which is formulated by Lyapunov Optimization. The market-based advantages of nanogrids with photovoltaic energy storage systems are discussed in [13].

In [14], different types of renewable and non-renewable resources like wind turbines, PVs, and fuel cells are taken into consideration in grid-connected nanogrids. Unlike other studies, the environmental damage cost of pollution gases and the power losses of batteries costs are considered in optimizing operation management process. A new multi-objective optimization model is proposed in [15] for energy management in microgrid/nanogrid to determine the time of buying or selling electricity to or from the main grid. Ref [16] aims to gain optimal daily scheduling of energy storage systems in microgrids, while the uncertainties associated with load and RESs available power as well as the time and duration of unscheduled islanding events are considered.

In [17] a robust programming that determine the optimal expansion of distribution networks with the penetration of EVs, where the aims are reinforcement/construction of substations and/or electrical vehicles charging stations, and determining the capacity of renewable resources, is represented. Note in [17] is that the uncertainty of the load and EV demand, which their level are changed in various time frames, is modeled through a normal distribution variable, so a scenario-based model like Mont Carlo simulation is required to solve the program. Ref [18] represents a dynamic programming (DP) technique to optimize power flow in solar-based DC nanogrid in presence of battery storage. In addition to an optimal power flow, that paper achieves maximum availability of the solar energy system, minimum fuel consumption and an increase in the battery life cycle.

TABLE I
TAXONOMY OF PLANNING AND ENERGY MANAGEMENT OF NANOGRIDS

References	Network level	Planning result			Bus type analysis	BES penetration	EVs penetration	Mathematical modeling
		Energy management	Optimal sizing	Generation mix				
[7]	nanogrid	✓	✓			✓		MILP
[8]	microgrid		✓	✓	✓	✓		MILP
[9]	microgrid		✓	✓	✓	✓		MILP
[10]	nanogrid	✓				✓		
[11]	nanogrid	✓	✓					NLP
[12]	nanogrid	✓						
[13]	nanogrid		✓			✓		LO
[14]	nanogrid	✓				✓		MO
[15]	nanogrid	✓				✓		LP
[16]	microgrid	✓				✓		MILP
[17]	EDS		✓	✓			✓	MILP
[18]	nanogrid	✓				✓		DP
This paper	nanogrid	✓	✓	✓	✓	✓	✓	MILP

LO= Lyapunov Optimization MO= Multi-Objective EDS= Electrical Distribution Systems DP= Dynamic Programming

D. Contributions

This work considers the following three issues and try to propose a new planning tool that is able to concurrently solve them: A) determining the optimal energy resources mix; B) determining the economically optimal type of the nanogrid (i.e. AC or DC; C) identifying threshold values of

BESs' maximum installation capacity, EVs' maximum discharge power rate, and DC loads which make the DC nanogrid a more economically viable solution than the AC nanogrid; and D) a 24-hour demand-side management which makes properly and optimally each energy resources to participate in supplying ENGs power demand.

The proposed nanogrid planning framework minimizes the total cost includes investment costs of energy resources and converters, cost/income of the imported/exported energy to the upstream network or neighbor nano-grids, income from the provision of the demand side response (DSR) services, AC/DC rectifiers, and DC/AC inverters, as well as the nanogrid operation costs. In brief, the main contributions of this paper can be recapitulated as follows:

- Optimal planning of the renewable energy resources and energy storage devices mix;
- Determination of the economically optimal types of nanogrid: AC or DC?;
- Determination of the optimal threshold ratios of BESs' maximum installation capacity, EVs' maximum discharge power rate, and DC loads which make the DC nanogrid a more affordable option than an AC one;
- Optimal day-ahead demand-side response (DSR) plan.

The remainder of the paper is organized as follows. Section II provides the proposed model and formulation while the numerical results of planning for three ENGs are presented in section III. Section IV analyses the results extracted from section III, and section V concludes the paper.

II. PLANNING FORMULATION

Fig. 2 and Fig. 3 show a complete architecture of DC and AC energy nanogrids respectively. At both types of ENGs, each ENG is connected to the upstream network through an AC common bus. At DC ENG, a bidirectional DC/AC converter is required to connect the AC common bus to the DC bus of ENG. EVs' parking lot, BES and solar power systems are connected to the DC bus through a DC/DC converter. In addition, the wind power system and AC load of ENG can be joined to DC bus using rectifier and inverter respectively.

At AC ENG, AC common bus and wind power system are connected to AC bus of ENG using a transformer. EVs' parking lot and BES are connected to the AC bus through a bidirectional DC/AC converter. It needs to install an inverter between the solar system and AC bus, and a rectifier to make the connection between DC load and AC bus.

In the proposed planning model, the total cost of ENGs, including investment, operation and maintenance costs, should be minimized to achieve an optimal type of ENG, size and generation mix. Therefore, the objective function of the proposed model is as follows:

$$C_{total} = \sum_{n} IC(n) + OC(n) + MC(n) \qquad (1)$$

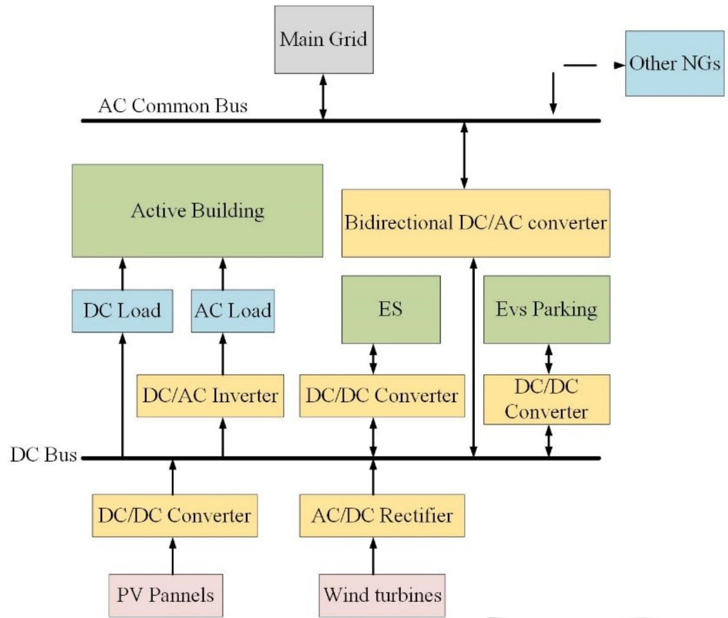


Fig. 2. Architecture of a DC nanogrid

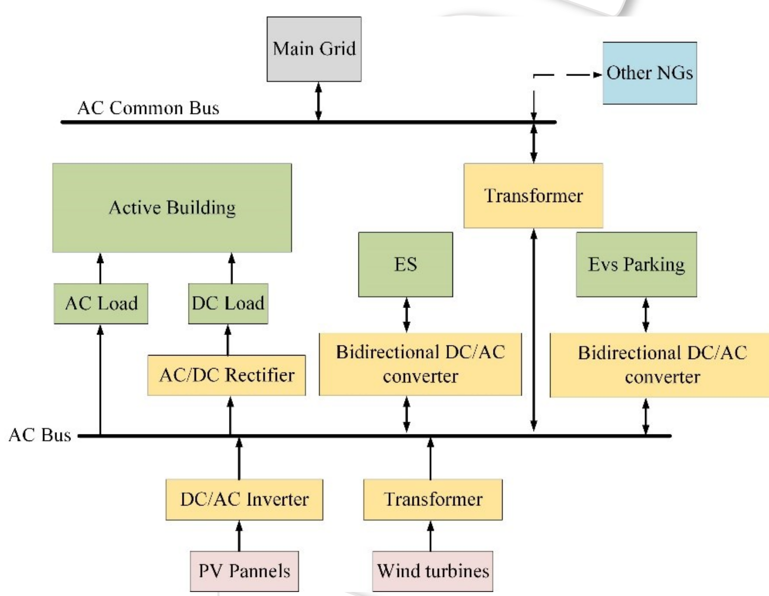


Fig. 3. Architecture of an AC nanogrid

The note is that, in this paper, the maintenance cost is only restricted to the maintenance of DERs and not include the maintenance cost of converters since it has been supposed that all converters are not repairable and they have to be replaced with a new ones after their lifetime which is the same as planning horizon. Investment cost includes the capital price of all DERs and converters, and can be written as two equations below based on ENG's type DC or AC.

$$
\begin{aligned}
&-B(1-A(n)) \le IC(n) - [\sum_y k(y) \sum_i CR(i)P(n,i) + \\
&\sum_y k(y)E(n)CS + \sum_y k(y)P(n,1)CRE + \sum_y k(y)P(n,2) \\
&CC + \sum_y k(y)(1-l(n))L^{\max}(n)CI + \sum_y k(y)P_{ch}^{\max}CC \\
&+\sum_y k(y)P_{ch,ev}^{\max}CC + \sum_y k(y)P_g^{\max}CB] \le B(1-A(n)) \qquad \forall n
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
&-BA(n) \le IC(n) - [\sum_y k(y) \sum_i CR(i)P(n,i) + \\
&\sum_y k(y)E(n)CS + \sum_y k(y)P(n,1)CT + \sum_y k(y)P(n,2) \\
&CI + \sum_y k(y)l(n)L^{\max}(n)CRE + \sum_y k(y)P_{ch}^{\max}CB \\
&+\sum_y k(y)P_{ch,ev}^{\max}CB + \sum_y k(y)P_g^{\max}CT] \le BA(n) \qquad \forall n
\end{aligned} \tag{3}
$$

According to Eq. 2, if planning prefers DC ENG, variable *A* would be 1 and (3) would be free; so, investment cost would be equal to (2). Conversely, if planning chooses AC ENG, variable *A* would be 0 and (2) would be free; so, investment cost would be equal to (3). It need to be mentioned that the DERs set (*i*) includes two members: wind power and photovoltaic power system. Therefore, *i*=1 indicates wind power system, and *i*=2 implies solar power system. The equations (4)-(6) below represent operation and maintenance costs, which are the cost of purchasing and selling energy from/to the upstream network, and of the DERs' repair and refurbishment, respectively, and the coefficient of the net present value.

$$
OC(n) = \sum_y k(y) \sum_d \sum_t C^p P_g(n,t) - \sum_y k(y) \sum_d \sum_t C^s P_c(n,t) \qquad \forall n \tag{4}
$$

$$
MC(n) = \sum_y k(y) M^w P(n,1) + \sum_y k(y) M^p P(n,2) \qquad \forall n \tag{5}
$$

$$
k(y) = 1 \Big/ (1+r)^{y-1} \qquad \forall y \tag{6}
$$

Other constraints can be divided into three categories as limits and constraints for power balance equation and generation of DERs, constraints of energy trading between ENGs and the upstream network; and constraints of BESs and EVs' station lots.

A. Power balance and generation

Equations and inequalities (7)-(12) represent generation-related constraints. (7) and (8) show the hourly power balance equations for both DC and AC ENGs during a day. Like investment cost equations, if planning prefers DC ENG, variable *A* would be 1, and (8) would be free; so the power balance equation would match (7). Conversely, if planning chooses AC ENG, variable *A* would be 0, and (7) would be free. As a result, power balance formulation would be equal to (8).

$$
\begin{aligned}
&-B(1-A(n)) \le Q[P_p(n,t)+P_w(n,t)+P_g(n,t)+P_s^{dis}(n,t) \\
&+P_{ev}^{dis}(n,t)] - Q[P_s^{ch}(n,t)+P_{ev}^{ch}(n,t)] - l(n)L(n,t) - \\
&(1-l(n))L(n,t)/Q - P_c(n,t)/Q \le B(1-A(n)) \qquad \forall n,t
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
&-BA(n) \le Q[P_p(n,t)+P_s^{dis}(n,t)+P_{ev}^{dis}(n,t)] \\
&+P_w(n,t)+P_g(n,t) - Q[P_s^{ch}(n,t)+P_{ev}^{ch}(n,t)] - \\
&l(n)L(n,t)/Q - (1-l(n))L(n,t) - P_c(n,t) \le BA(n) \qquad \forall n,t
\end{aligned} \tag{8}
$$

Inequality (9) states that DERs in each ENG must at least be able to supply a predefined specific load known as the critical load at any time. (10) and (11) represent the output power limit for DERs, and γ is a value less and equal than 1 that implies sunlight intensity during the day which is 0 in the absence of the sun and is 1 at noon. (12) explains the upper and lower limits for an installed capacity of DERs, and (13) shows that it is obligatory for an ENG to have at least one kind of DERs.

$$\sum_i P(n,i) \ge \alpha L^{\max}(n) \qquad \forall n \tag{9}$$

$$P_w(n,t) \le \beta P(n,1) \qquad \forall n,t \tag{10}$$

$$P_p(n,t) \le \beta \gamma(t) P(n,2) \qquad \forall n,t \tag{11}$$

$$I_R(n,i)P^{\min}(n,i) \le P(n,i) \le I_R(n,i)P^{\max}(n,i) \qquad \forall n,i \tag{12}$$

$$\sum_i I_R(n,i) \ge 1 \qquad \forall n \tag{13}$$

B. Energy Trading Constraints

Inequalities (14) and (15) restrict power trading between ENG and upstream network to their bounds, and (16) represents that to sell and purchase energy to/from network may not be happened simultaneously.

$$I_g(n,t)P_g^{\min} \le P_g(n,t) \le I_g(n,t)P_g^{\max} \qquad \forall n,t \tag{14}$$

$$I_c(n,t)P_s^{\min} \le P_c(n,t) \le I_c(n,t)P_s^{\max} \qquad \forall n,t \tag{15}$$

$$I_g(n,t)+I_c(n,t) \le 1 \qquad \forall n,t \tag{16}$$

C. BES and EV constraints

Constraints (17)-(26) explain BES's limit. (17)-(19) represent that installed energy capacity, charge, and discharge power rates of BES must not exceed their bounds. Constraint (20) implies that batteries of BES can not be charged at the same time as discharge.

$$E_s^{\min} \leq E(n) \leq E_s^{\max} \qquad \forall n \tag{17}$$

$$I_s^{ch}(n,t)P_{ch}^{\min} \leq P_s^{ch}(n,t) \leq I_s^{ch}(n,t)P_{ch}^{\max} \qquad \forall n,t \tag{18}$$

$$I_s^{dis}(n,t)P_{dis}^{\min} \leq P_s^{dis}(n,t) \leq I_s^{dis}(n,t)P_{dis}^{\max} \qquad \forall n,t \tag{19}$$

$$I_s^{ch}(n,t) + I_s^{dis}(n,t) \leq 1 \qquad \forall n,t \tag{20}$$

Equations (21) and (22) show hourly available energy at the storage system, while (23)-(25) restrict this energy to its upper and lower limits. Inequality (26) tries to prevent the energy of the last hour at BES from not being much more or lower than that of the first time.

$$e_s(n,t) = e_s(n,t-1) + P_s^{ch}(n,t)Q - P_s^{dis}(n,t)/Q \qquad \forall n,t>1 \tag{21}$$

$$e_s(n,t) = U_s(0) + P_s^{ch}(n,t)Q - P_s^{dis}(n,t)/Q \qquad \forall n,t<2 \tag{22}$$

$$e_s^{\min}(n) \leq e_s(n,t) \leq e_s^{\max}(n) \qquad \forall n,t \tag{23}$$

$$e_s^{\min}(n) = zE(n) \qquad \forall n \tag{24}$$

$$e_s^{\max}(n) = ZE(n) \qquad \forall n \tag{25}$$

$$U_s(0) - \Delta U_s \leq e_s(n,t) \leq U_s(0) + \Delta U_s \qquad \forall n,t>23 \tag{26}$$

The rest of the inequalities refer to EVs in which (27)-(33) have approximately the same definition as those for BES because EVs can operate like BES meaning their batteries can be charged through grid or ENG and can be discharged to help the supply of ENG's load demand or sell energy to the upstream grid. (34) and (35) point that when EVs are out of ENG (parking lot) can not be charged and discharged. Finally, (36) explains that EVs have to be charged with the minimum energy needed to be out of ENG.

$$I_{ev}^{ch}(n,t)P_{ch,ev}^{\min} \leq P_{ev}^{ch}(n,t) \leq I_{ev}^{ch}(n,t)P_{ch,ev}^{\max} \qquad \forall n,T_{in} \tag{27}$$

$$I_{ev}^{dis}(n,t)P_{dis,ev}^{\min} \leq P_{ev}^{dis}(n,t) \leq I_{ev}^{dis}(n,t)P_{dis,ev}^{\max} \qquad \forall n,T_{in} \tag{28}$$

$$I_{ev}^{ch}(n,t) + I_{ev}^{dis}(n,t) \leq 1 \qquad \forall n,t \tag{29}$$

$$e_{ev}(n,t) = e_{ev}(n,t-1) + P_{ev}^{ch}(n,t)Q - P_{ev}^{dis}(n,t)/Q - P_{ev,out}^{dis}(n,t) \qquad \forall n,t>1 \tag{30}$$

$$e_{ev}(n,t) = U_{ev}(0) + P_{ev}^{ch}(n,t)Q - P_{ev}^{dis}(n,t)/Q - P_{ev,out}^{dis}(n,t) \qquad \forall n,t<2 \tag{31}$$

$$U_{ev}^{\min} \leq e_{ev}(n,t) \leq U_{ev}^{\max} \qquad \forall n,t \tag{32}$$

$$U_{ev}(0) - \Delta U_{ev} \leq e_{ev}(n,t) \leq U_{ev}(0) + \Delta U_{ev} \qquad \forall n,t>23 \tag{33}$$

$$P_{ev}^{ch}(n,t) = 0 \qquad \forall n, T_{out} \tag{34}$$

$$P_{ev}^{dis}(n,t) = 0 \qquad \forall n, T_{out} \tag{35}$$

$$e_{ev}(n,t) \geq N\lambda D(n) \qquad \forall n, T_l \tag{36}$$

In this paper a mixed-integer linear programming (MILP) formulation is considered to solve optimal planning for residential energy nanogrids including DERs' mix and size, determining the type of ENGs (DC or AC) and 24-hourly optimal power flow under different situations and scenarios.

III. NUMERICAL STUDY

To illustrate the performance and benefits of the proposed planning model, three residential buildings are considered as three ENGs which are connected to the upstream network through an AC bus (see Fig. 2 or Fig.3). Each ENG is a residential tower with a parking lot for hybrid electric vehicles which is able to charge and discharge them. In addition, there are 100 units at ENGs each, and it is assumed that all units have an EV. The ENGs are supposedly located in Australia and the load data has been extracted from 300 residential customers in Australia [19]. Fig. 4 displays the hourly load of the three under study ENGs.

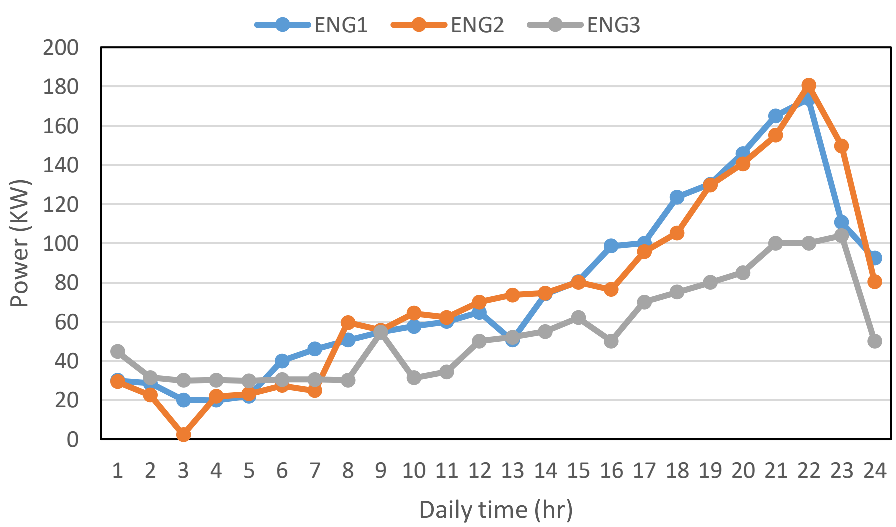


Fig. 4. Hourly Demand of Residential ENGs

The Mitsubishi SUV (6 charge hour, 240 V, 10 A, 54 Km, 12 KWh) as one of the popular Plug-in Hybrid Electrical Vehicles (PHEVs) is selected for this study [20]. Data related to the average daily journey in Australia is found in [21]. Planning horizon, discount rate, coefficient of upper and lower energy limit for BES, and the time at which EVs leave ENGs are 10 years, 0.1, 0.1, 0.9, and 6:00 AM, respectively. EVs are supposed to go back home at 8:00 PM, so can charge and discharge before 6 AM. Investment and maintenance cost of DERs and BES, and investment cost of converters have been drawn from [22], [23], [24], and [25]. The set of DERs and converters are provided in Table II.

TABLE II
CHARACTERISTICS OF CONVERTERS AND DERS

Converters, BES, and DERs	Investment cost ($/KW(h))	Maintenance cost ($/KW)
Inverter	58	
Rectifier	40	
DC/DC converter	65	
Bidirectional DC/AC	80	
Transformer	30	
BES	100	
Wind turbine	2800	30
PV system	2000	20

As it was said before, the main goal of this paper is to evaluate how some parameters can change the type of ENG, the mix of generation, and optimal planning and operation of ENGs. In this study, these parameters are the rate of DC load at ENGs, change in the maximum installed capacity of BES, and the maximum discharge power rate of EVs. Therefore, four cases as follows are set to assess these aims.

A. Baseline Case

This is the first and basic case of programming. In this case, the rate of DC load for all three ENGs is 0.5, the upper bound for permissible installation capacity of BES is set on the highest value meaning 800 KWh, and the maximum discharge power rate of EVs to support demand-side response is considered its peak that is 200 KWh. The results of the planning for this case are represented in Table III.

TABLE III
PLANNING RESULTS OF CASE BASE

ENGs	A	PV installed capacity (KW)	Wind installed capacity (KW)	BES installed capacity (KWh)	Investment cost ($)	Operation cost ($)	Maintenance cost ($)
ENG 1	0	145.5	0	774	3040706.1	9364.4	23715.8
ENG 2	0	100	0	774	2910217	18792.7	22322.5
ENG 3	0	0	100	774	2185093.76	416083	13518

B. case 1

In this case, the effect of change in the rate of DC load at three ENGs on the type of nanogrid, DERs' mix and capacity; investment and operation costs; and daily power flow at ENGs are evaluated. This parameter α increases from 0.4 to 1 by 0.2 steps. Other parameters are set on their basic values as those in the case base. The results of the planning in case 1 are shown in Table IV.

C. case 2

This case analysis how an increase in the upper bound for allowable installation capacity of BES can change the type of ENG, the mix and capacity of generation and investment and operation costs, and the way that electrical energy flows as well. This parameter E_s^{max} rises from 200 to 800 KWh by 200 KWh steps. The rate of DC load and availability peak of EVs' discharge power are put on their basic amount (0.5, 200 KWh). Table V shows the planning consequences of this case.

TABLE IV
PLANNING RESULTS OF CASE 1

α	ENGs	A	PV installed capacity (KW)	Wind installed capacity (KW)	BES installed capacity (KWh)	Investment cost ($)	Operation cost ($)	Maintenance cost ($)
0.4	ENG 1	0	116.9	0	774	3035341.4	37745.7	23708.7
	ENG 2	0	110	0	774	2712376	26028.1	20277
	ENG 3	0	0	100	774	2182284.7	410684.1	13518
0.6	ENG 1	1	123.4	0	774	3136466.9	39280.4	25033.4
	ENG 2	1	100.8	0	774	2699869.2	128717.4	20438.8
	ENG 3	0	0	100	774	2187902.8	421481.9	13518
0.8	ENG 1	1	120	0	774	3057498.4	49184	24343
	ENG 2	1	100	0	774	2670392.7	97749.3	20277
	ENG 3	1	0	100	774	2170622.9	444151.3	13518
1	ENG 1	1	118.1	0	774	3006967.9	14731.4	23953
	ENG 2	1	100	0	774	2656232.8	86900.1	20277
	ENG 3	1	0	100	774	2162476.7	432238.7	13518

D. case 3

This case assesses how increase in maximum discharge power rate of EVs can change the type of ENG; the mix and size of generation units; investment and operation costs; and 24-hour power flow. It is obvious that EVs may not supply ENGs demand power with their maximum discharge energy rate because of being out of parking lot and unexpected events. This type of flexible resources' behavior is largely unpredictable. So, this paper considers changes in the availability amount of this parameter ($P_{dis,ev}^{max}$) rather than stochastic approaches. This parameter $P_{dis,ev}^{max}$ rises from 50 to 200 KW in 50 KW steps. The rate of DC load and upper bound for installation capacity of BES are fixed on their basic values (0.5, 800 KWh). Table VI illustrates the planning results for this case.

TABLE V
PLANNING RESULTS OF CASE 2

E_s^{max}(KWh)	ENGs	A	PV installed capacity (KW)	Wind installed capacity (KW)	BES installed capacity (KWh)	Investment cost ($)	Operation cost ($)	Maintenance cost ($)
200	ENG 1	0	145.5	0	190.1	3191888.6	-130717.6	29502.5
	ENG 2	0	100	0	190.1	2322565.1	50415.2	20277
	ENG 3	0	0	100	190.1	1790400.1	425971.7	13518
400	ENG 1	0	101.1	0	390	2479171.3	94515.8	20514.2
	ENG 2	0	100	0	390	2457745.6	27575.6	20277
	ENG 3	0	0	100	390	1925580.6	413256.4	13518
600	ENG 1	1	123.4	0	579	3011429.7	25698	25033.4
	ENG 2	0	110	0	579	2585416	24473.2	20277
	ENG 3	0	0	100	579	2053251	409859.3	13518
800	ENG 1	0	116.9	0	774	3040706.1	9364.4	23715.8
	ENG 2	0	110	0	774	2910217	18792.7	22322.5
	ENG 3	0	0	100	774	2185093.7	416083	13518

TABLE VI
PLANNING RESULTS OF CASE 3

$P_{dis,ev}^{max}$	ENGs	A	PV installed capacity (KW)	Wind installed capacity (KW)	BES installed capacity (KWh)	Investment cost ($)	Operation cost ($)	Maintenance cost ($)
50	ENG 1	0	117.8	0	774	3058044.3	10856	23899.6
	ENG 2	0	100	0	774	2717258.7	37494.9	20277
	ENG 3	0	0	100	774	2185093.7	416083	13518
100	ENG 1	0	119.1	0	774	3083212.8	33947.2	24166.4
	ENG 2	0	100	0	774	2717258.7	30403.8	20277
	ENG 3	0	0	100	774	2185093.7	416083	13518
150	ENG 1	0	17.8	0	774	3058044.3	7099.6	23899.6
	ENG 2	0	111.2	0	774	2932775.4	-7633.9	22561.7
	ENG 3	0	0	100	774	2185093.7	416083	13518
200	ENG 1	0	116.95	0	774	3040706.1	9364.4	23715.8
	ENG 2	0	110	0	774	2910217	18792.7	22322.5
	ENG 3	0	0	100	774	2185093.7	416083	13518

IV. CASE STUDY ANALYSIS

Starting from the case base, as can be seen from Table III, it is noticeable that the program would choose AC type for all three ENGs ($A = 0$) because, in this common occasion, the cost of all converters in DC ENG is totally more expensive than that of an AC one. Energy resources for supplying customers at two first ENGs is the solar power system, while here is wind power system for ENG3. Since the installed capacity of PV systems at ENG1 and ENG2 are larger than wind system at ENG3, investment and maintenance cost of ENG1 and ENG2 are much more than those of at ENG3.

looking at both table III and figure 5 Simultaneously, Although solar systems can not generate energy at the absence of sun (night hours) and the peak load at these ENGs are larger than ENG3, program would prefer to install solar power system for both ENG1 and ENG2. There are two reasons: first, the investment cost of the solar system is lower than wind ones, and second is that they can sell electrical energy to the upstream network at noon which leads to a considerable decrease in operation cost. To reach a balance between operation and investment cost, the program would rather set lower wind power generation than peak load at ENG3. In this case ENG's load is provided at peak hours through purchasing energy from upstream network. Therefore, operation cost at this nanogrid has a meaningful value.

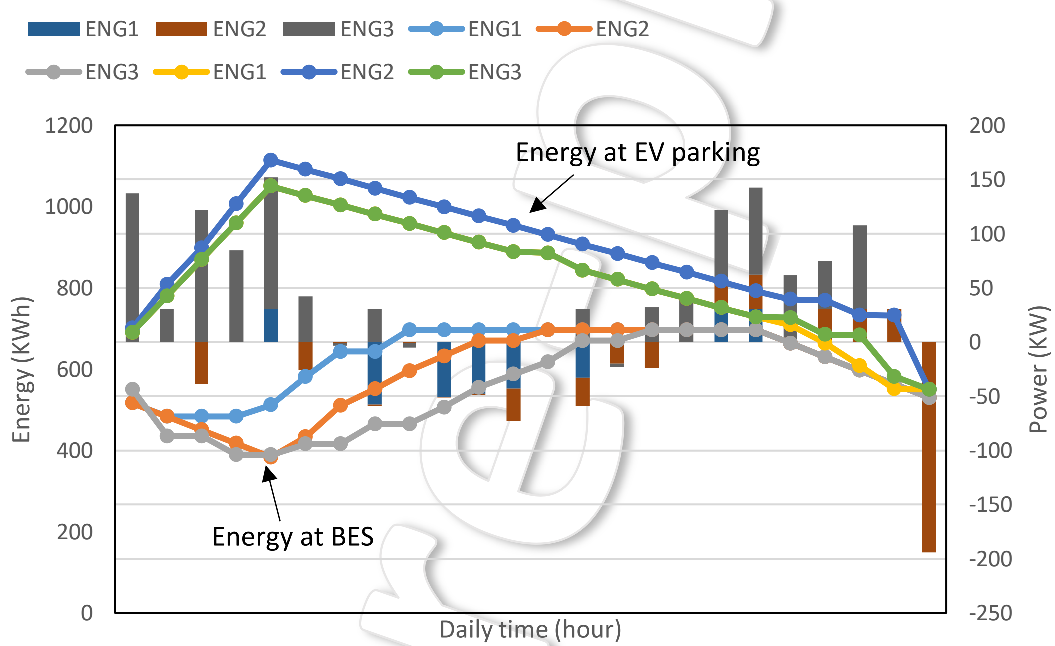


Fig. 5. Daily energy and power trading at case base

Figure 5 illustrates Daily energy at the BES system and VEs parking (line graphs) and daily power trading (bar charts) at the case base. It is worth saying, due to the fact that all ENGs are residential buildings with similar load behavior, these variables at each building would change as other. It can be derived that electrical vehicles in parking lot, unlike batteries at BES system, are charged at early hours of a day. This is reasonable because EVs should be prepared to go out till 20 PM. after that they can share their energy to supply load and/or trade with the main grid. Conversely, the BES system is discharged at the first hours to help to supply ENGs' load, then it is charged to peak hours, largely by PV systems for ENG1 and ENG2 and by purchasing energy from the main grid for ENG3. Finally, it has the same trend as EVs during peak hours. Figure 5 represents the reason why operation cost at ENG3 is significantly more than other ones. It mostly receives electrical energy from the upstream network during a day which causes to drop in DER's investment cost.

Looking at Table IV, some points can be extracted. First, as expected, a change in the rate of DC load affects the type of ENGs. An increase in the rate of DC load, according to investment cost equation for DC ENG (Eq. 2), results in a decrease in the term related to the inverter in this equation, and in the case $l(n) = 1$, where there is no AC load, it would be deleted. Conversely, according to (3), the term of investment cost for rectifier rises when l increases. So, investment cost in DC state would be much lower than that in AC one. Power balance equations can also make this analysis more clear. In fact, when l surges, considering converters efficiency, DC ENG needs less energy purchased from the upstream grid and/or other resources to supply customers than AC ENG. Therefore, DC ENG would be more optimal than AC one. Since the peak load at ENG1 and ENG2 is more than ENG1, less increase in l at the first two ENGs makes a more considerable decrease in investment cost. So, optimal threshold ratios of l for ENG 1 and ENG2 is 0.6 and is 0.8 for ENG3.

The second point is that due to not change in demand and upper bound of capacities, the mix generation and installed capacity of DERs and BES have not been modified. So, investment and maintenance costs have not approximately changed, and these little fluctuations in Table IV are because of an increase in l; therefore, non-meaningful change in investment cost of rectifiers and inverters is carried out.

Another point in Table IV is operation cost. That is an abrupt increase in operation cost of ENG2 by l increment from 0.4 to 0.6. There is an acceptable reason which is that because the type of the ENG is changed, and considering the power balance equation in DC state (see (7)), converters' efficiency makes the ENG buy more energy from the upstream network. In addition, since to sell and purchase energy to/from the upstream network might not be done simultaneously, the operation cost would increase (see (4)).

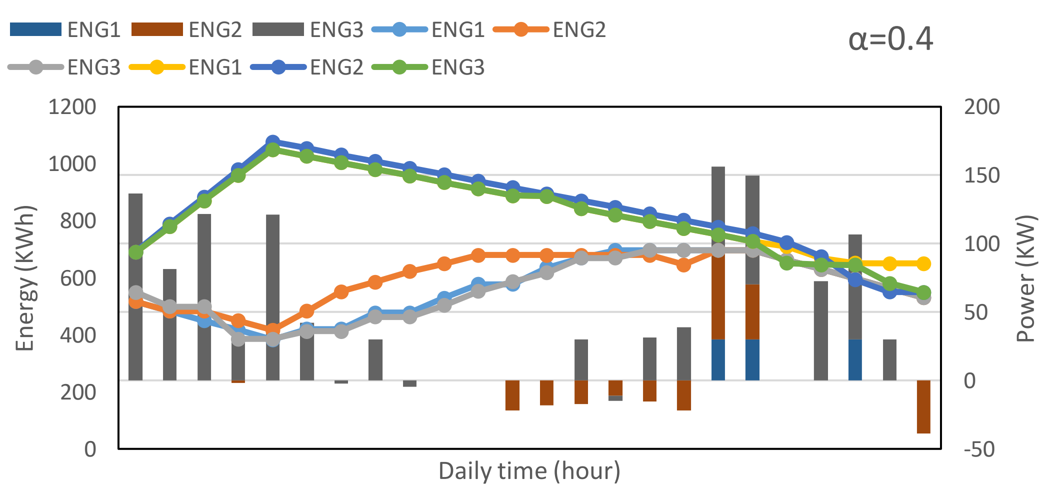
The same assessment is valid for an increase in operation cost at ENG1, while due to higher peak load at it than ENG2, it rises when l goes up excepting in $l(n) = 1$ for AC load term in operation equation, which is connected to converter in DC power balance equation (see (7)) would be disappeared, so there would be less need to purchase energy. Nevertheless, its noticeable drop once l rises from 0.8 to 1 is that the term of AC load.

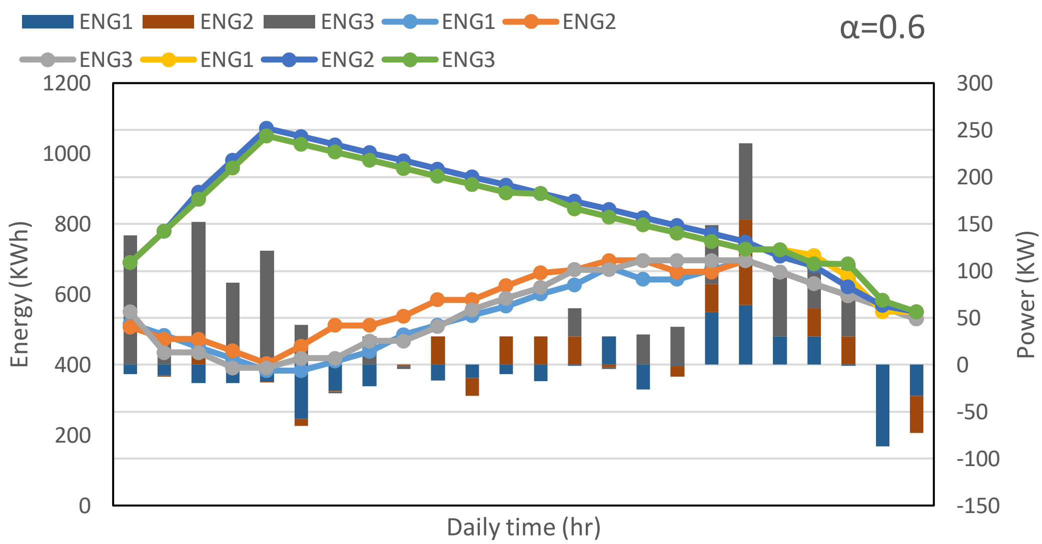
This could be seen clearer from the bar chart of figure 6 showing trading energy between ENGs and the main grid. It could be said that, although wind power system output is not restricted by environmental parameters like PV system, ENG3 would almost buy energy all hours a day from the main grid; the convincing reason is expensive investment cost for this system. According to the line graph of figure 6, it is expected, a different value of DC load rate may not make any noticeable change in energy stored at BES and EV parking because they are largely limited by their local parameters.

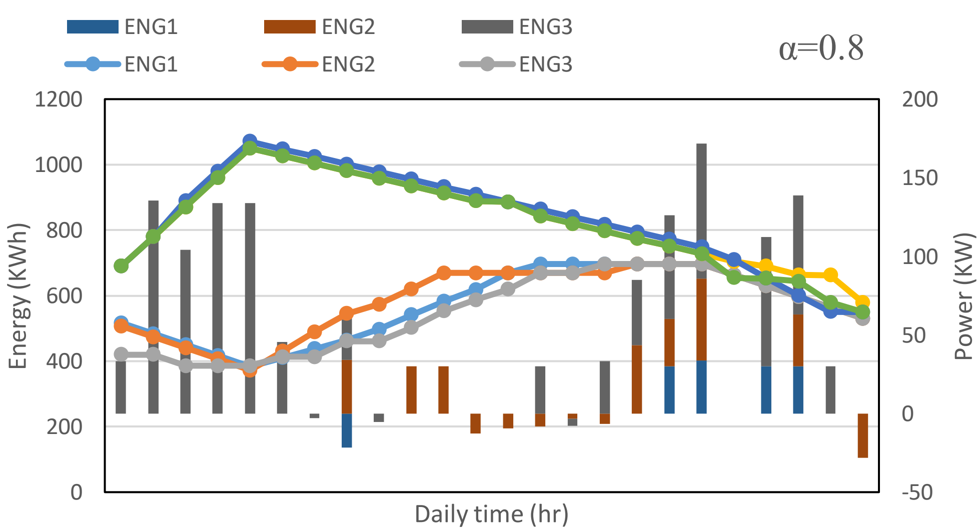
In case 2, looking at Table V, the impact of change in the upper bound of installed capacity of BES has been assessed. It was projected that a rise in E_s^{max} may not make a considerable difference in the type of ENGs since both DC and AC investment cost equations (see (2) and (3)) have the term related to BES's investment cost in common. Once $E_s^{max} = 600\ KWh$, the type of ENG1 is DC which is caused by a change in the pattern of BES's charge and discharge so that it can decrease operation cost in DC state.

Another predictable point is that once $E_s^{max} = 200\ KWh$, ENG1, that have more peak load than other ones, must use a solar power system with more installed capacity; this has to lead to a remarkable surge in investment cost at this ENG. Note that this rise in capacity of the solar system is so much that the amount of electrical energy which the ENG sells to the upstream network is more than that the ENG purchases from it; therefore, the operation cost at this ENG is negative. It can be seen that, the more amount for E_s^{max}, the more available energy for selling, and the less need to buy energy from the upstream grid. So, operation costs would decrease. While, for ENG2 and ENG3, Change in E_s^{max}, according to Table V, might not make any sensible change in the installed capacity of DERs. As a result, maintenance costs at these ENGs remind stable. When this parameter increases, investment cost at these two ENGs rises due to an increase in the cost of BES, whereas their operation cost dips because of more sold and less purchased energy.

From the line graph of figure 7, it is obvious that higher E_s^{max} availability has caused the more installed capacity of the BES system. Another remarkable point is that increase in the hourly available energy at EVs parking due to an increase in the amount of energy at BES, they can share their batteries to supply load power or sell to the main grid, making ENGs, especially at ENG3 for its lower peak load than others, to not need EVs to deliver energy. The bar chart of figure 7 advocates the evaluation above for case 2. ENG1 with much-installed capacity sells considerable energy to the main grid. When $E_s^{max} = 400\ KWh$, it has a wild drop, making ENG1 not trade energy with the upstream network. $E_s^{max} = 600\ KWh$ leads to higher capacity of the solar system, and to more balance trading. Considering both bar chart and Table V, because the generation capacity at ENG3 is low and constant, more capacity of BES system does not considerably change energy trading pattern but increases in investment cost.




ENG1
ENG2
ENG3
ENG1
ENG2
ENG3
ENG1
ENG2
ENG3
α=0.6
1200
1000
800
600
400
200
0
Energy (KWh)
300
250
200
150
100
50
0
-50
-100
-150
Power (KW)
Daily time (hr)


ENG1
ENG2
ENG3
ENG1
ENG2
ENG3
α=0.8
1200
1000
800
600
400
200
0
Energy (KWh)
200
150
100
50
0
-50
Power (KW)
Daily time (hr)

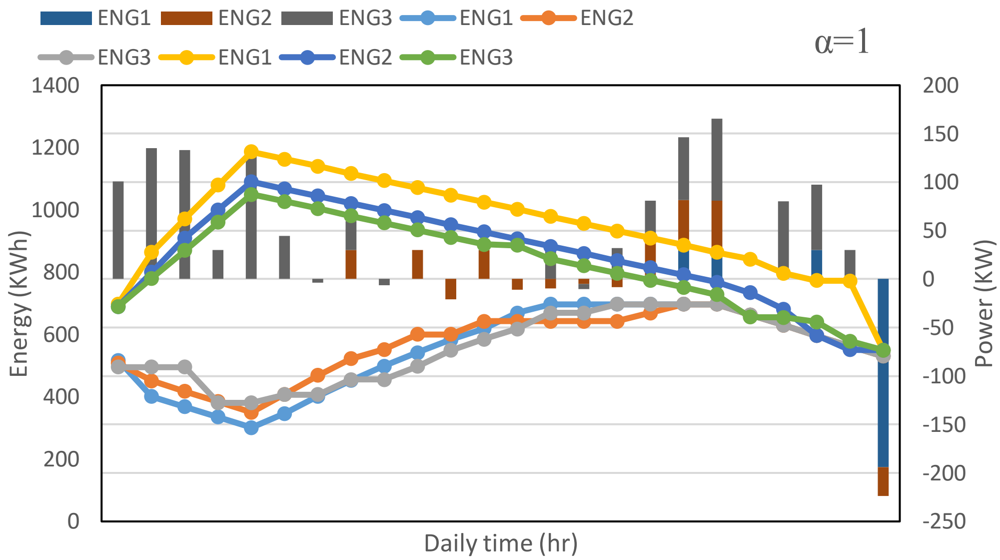


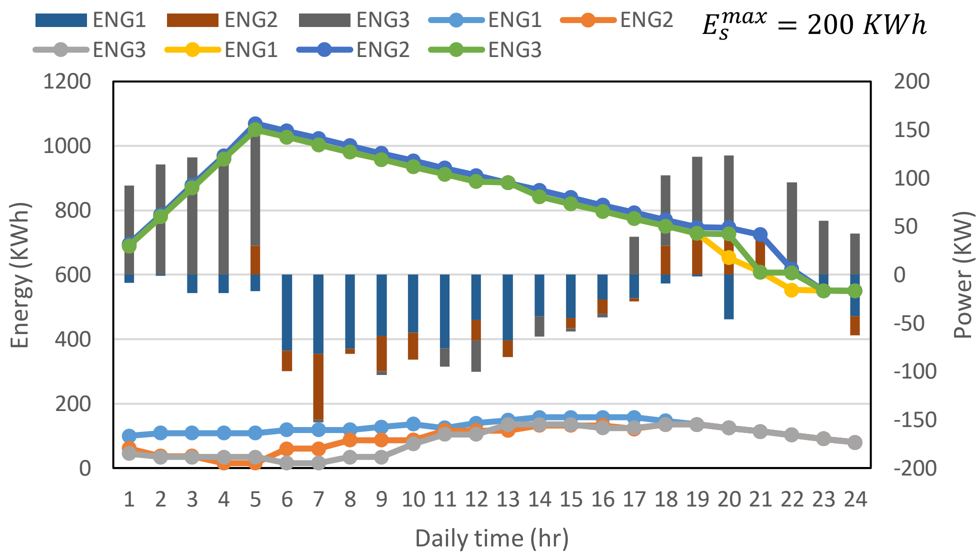
Fig. 6. Daily energy management at case 1: energy available at BESs and EVs parking, and power trading between ENGs and upstream network

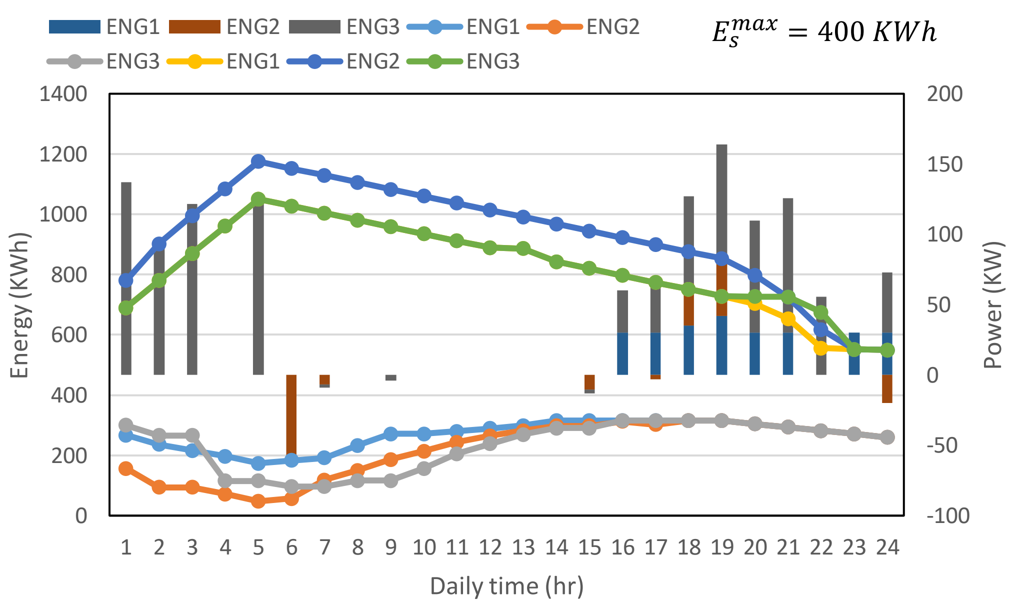
Table VI shows how different levels of availability for EVs' discharge power ($P_{dis,ev}^{max}$), which may happen each hour, affecting generation mix and costs. As can be seen, the increase and decrease in this parameter might not change the type of ENGs and the three buildings are all AC nanogrids. This is predictable because changes in this parameter would be similar and common in both DC and AC investment cost and power balance relationships. On the other hand, Changes in this parameter do not have a significant impact on the type and amount of ENGs' generation systems' installed capacity and the capacity of the BES. Consequently, investment and maintenance costs would not have meaningful variation.

As expected, since EVs should help supply customers' demand at peak load hours, and should be charged in the early hours of the day, so change in maximum EVs' discharge power can only affect DERs' hourly power generation pattern and operation cost. At ENG1, once $P_{dis,ev}^{max}$ is not more than 50 KW, The operation cost is low because there is not enough power available from EVs, so no need to charge them and buy much electricity from the upstream network. As a result, surplus electricity from the storage system can be sold.

By increasing $P_{dis,ev}^{max}$ to 100 KW, it reduces power sales and increases energy purchasing as EVs' charging increases. At higher values of this parameter, although the amount of charging power of EVs rises, EVs at peak load can assist generation systems in providing energy for customers, decreases power purchase, and rises the sale. As a result, the operating cost is reduced again. The bar chart in figure 8 supports this idea; when $P_{dis,ev}^{max} = 100$ KWh, purchasing electrical energy is considerably much, whereas for other amounts of this parameter, selling energy would overcome receiving it from the main grid.

Another noticeable point is the operation cost at ENG2. When $P_{dis,ev}^{max} = 150$ KW, The capacity of the solar system has also increased slightly. So, the pattern of power generation and distribution at the building has changed.


ENG1
ENG2
ENG3
ENG1
ENG2
ENG3
ENG1
ENG2
ENG3
$E_s^{max} = 200\ KWh$
Energy (KWh)
Power (KW)
Daily time (hr)


ENG1
ENG2
ENG3
ENG1
ENG2
ENG3
ENG1
ENG2
ENG3
$E_s^{max} = 400\ KWh$
Energy (KWh)
Power (KW)
Daily time (hr)

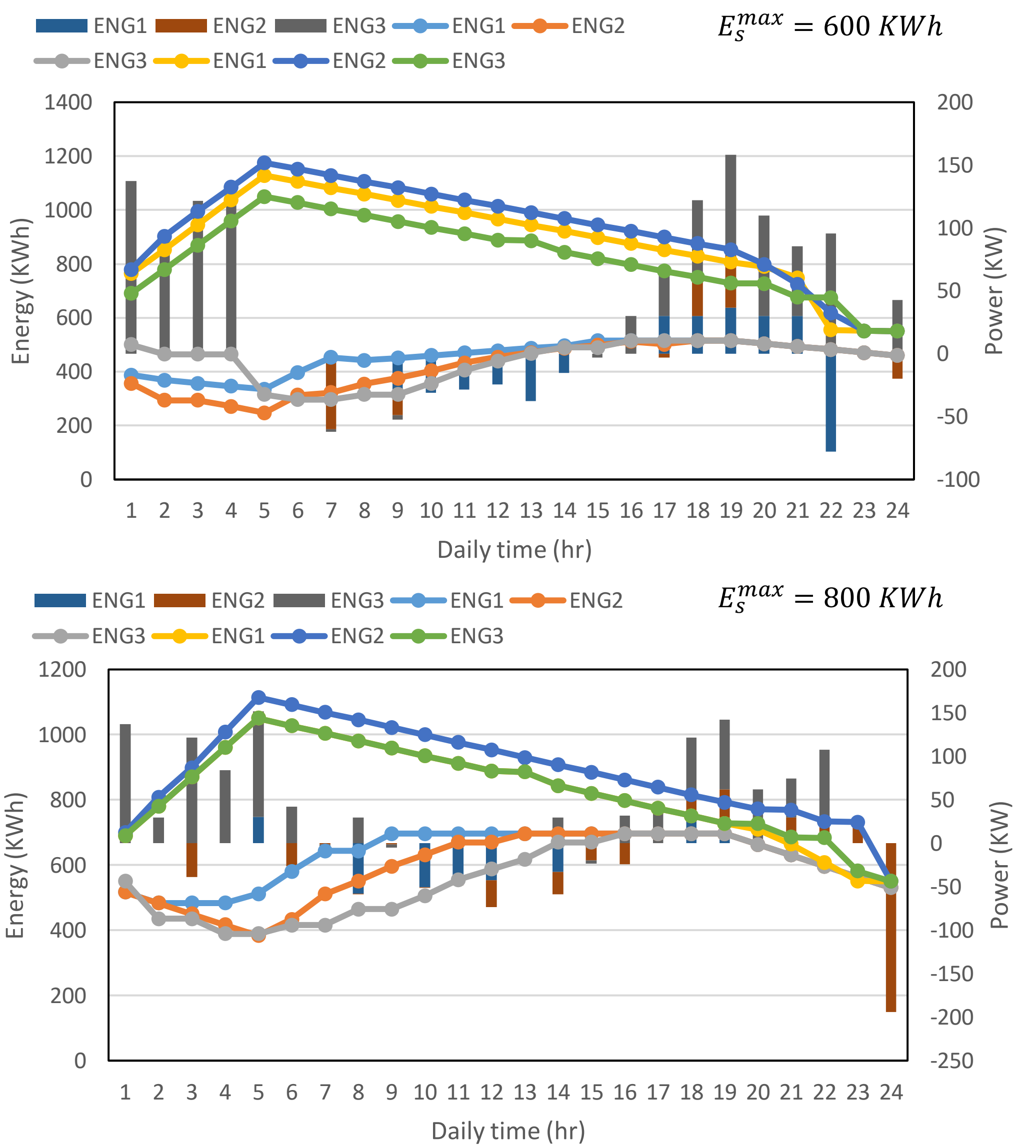
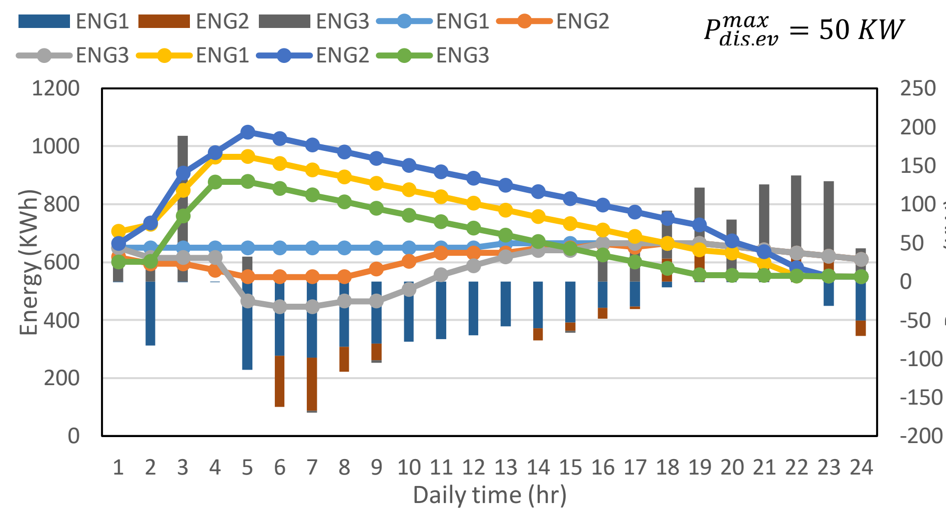
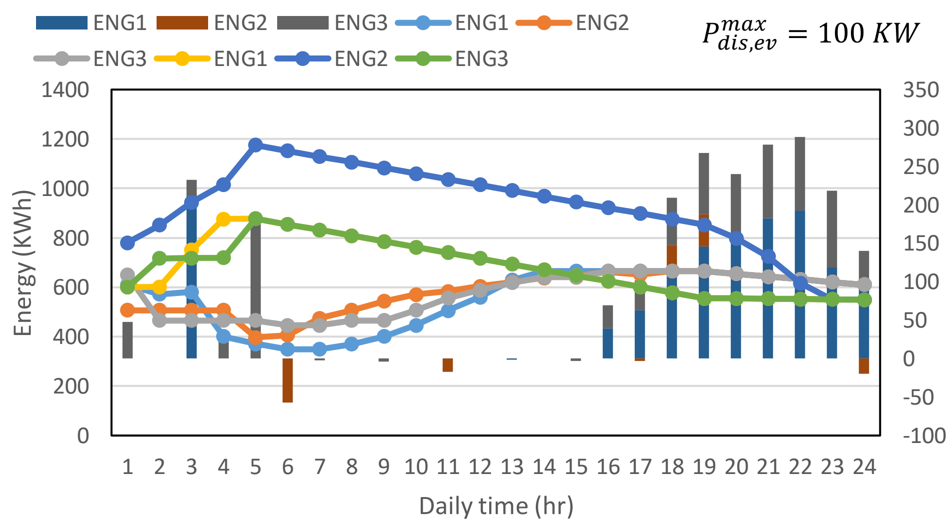


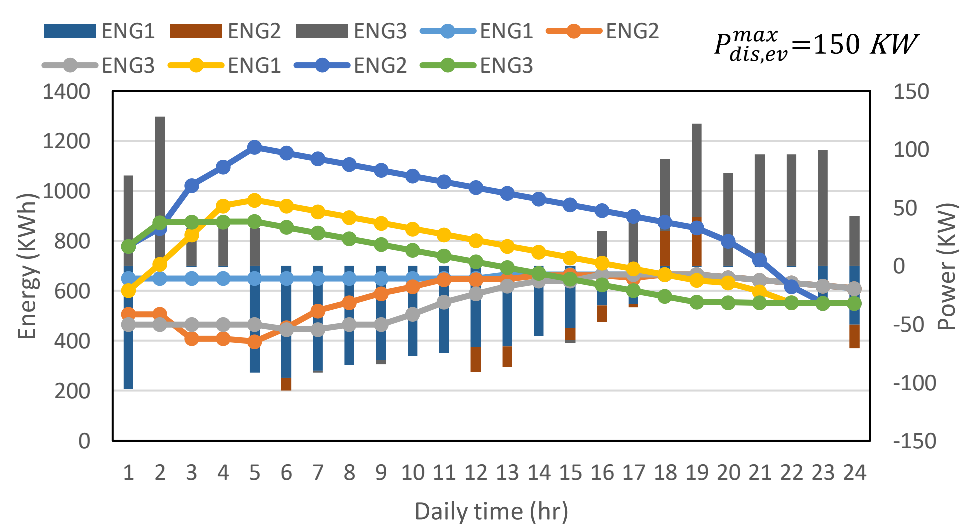
Fig. 7. Daily energy management at case 2: energy available at BESs and EVs parking, and power trading between ENGs and upstream network

In this case, EVs at ENG2 assist solar power systems at peak load, and since the capacity of the solar system has increased, so there is little need to buy electricity from the grid to charge EVs in the early hours of the day. These reasons have led to a negative operation cost at this ENG. looking at both table IV and bar chart of figure 8, it is interesting that, although the increase in $P_{dis,ev}^{max}$ at ENG3 may affect delivering and receiving electrical energy to/from the main grid, the operation cost of this active building would not vary in total. This implies that EV parking has a neutral influence on the operation, generation mix, and the type of active building at ENG3.

The line graph at figure 8 shows that for all amount of $P_{dis,ev}^{max}$, BES system at three active buildings have to deliver electrical energy at early hours to help charging EVs parking to be prepared going out, with the exception of $P_{dis,ev}^{max} = 50$ KW and $P_{dis,ev}^{max} = 150$ KW at ENG1 at which energy storage at BES is stable. It is expected that, increase in $P_{dis,ev}^{max}$ would support the generation system to supply the demand power, making EVs discharge their energy. This pattern definitely results in more charging at ENGs by purchasing from the main grid, DERs generation, and BES system. However, because the load at ENG1 and ENG3 at early hours of the day is more than that of ENG2, energy at parking at ENG1 and ENG3 dips first, then rises as ENG3.







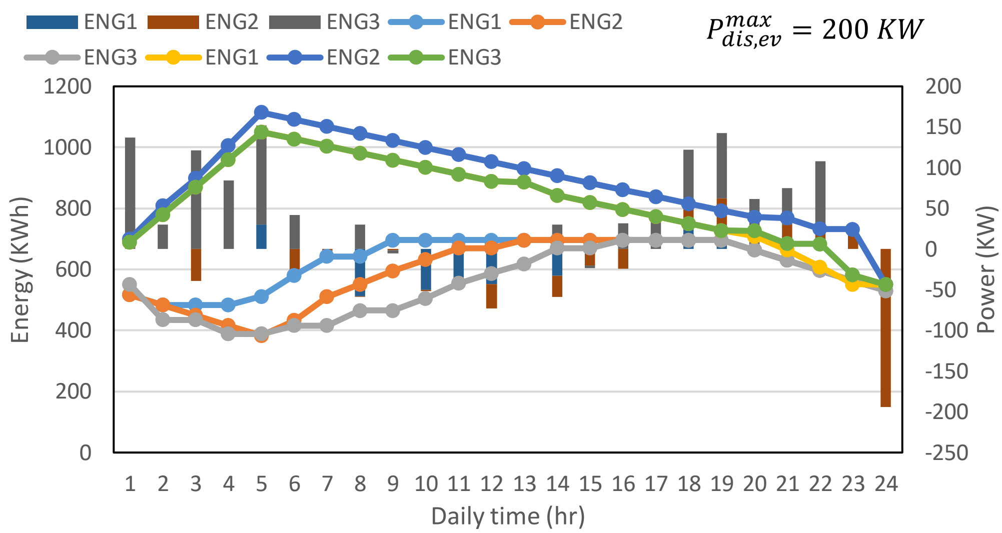


Fig. 8. Daily energy management at case 3: energy available at BESs and EVs parking, and power trading between ENGs and upstream network

V. CONCLUSION

This paper presents a planning framework for active buildings as an Energy Nano-Grid (ENG). The main goals of this paper are determining the optimal size and the generation mix of energy resources, the ENG type which is able to be either AC or DC, as well as the optimal energy management (EM). To implement a deep assessment, three factors: ratio of DC load, maximum allowable installation capacity of BES, and upper bound of EVs' discharge power availability, have been considered as three cases. According to the results, the type of ENGs would be DC when the rate of DC load increases, through reducing investment and operation costs. Whereas, stability at demand and bounds of capacities have caused this parameter to not have considerable influence on mix generation, the capacity of DERs and BES, and energy at EVs parking. Unlike DC load rate, the maximum capacity bound of the BES system can directly change the installed capacity of BES, the capacity of DERs, investment, and operation cost since it plays an important role, sometimes as a power supply resource and sometimes as a load. So, it might modify the pattern of generation and load. Due to not have a significant role at ENGs during the whole day, different level of EVs' maximum discharge power has not made any meaningful changes at generation mix and investment cost. However, it could only change the power supply at peak hours. So, operation cost and discharge power of EVs parking are only factors that vary noticeably.

REFERENCES

[1] World Energy Council in partnership with OLIVER WYMAN. (2018) World energy trilemma index 2018. [Online]. Available: https://www.worldenergy.org/wp-content/uploads/2018/ 10/World-Energy-Trilemma-Index-2018.pdf

[2] The Active Building Centre (ABC). (2018) EPSRC. [Online]. Available: https://www.activebuildingcentre.com/

[3] S. Senemar, A. Seifi, and M. Rastegar, Optimal Operation of Renewable- Based Residential Energy Hubs for Minimizing PV Curtailment. Cham: Springer International Publishing, 2018, pp. 271–295. [Online]. Available: https://doi.org/10.1007/978-3-319-75097-2 12

[4] S. Bracco, F. Delfino, G. Piazza, F. Foiadelli, and M. Longo, "Nanogrids with renewable sources, electrical storage and vehicle-to-home systems in the household sector: Analysis for a single-family dwelling," in 2019 IEEE Milan PowerTech. IEEE, 2019, pp. 1–6.

[5] W. Tushar, T. K. Saha, C. Yuen, D. Smith, and H. V. Poor, "Peer-topeer trading in electricity networks: an overview," IEEE Transactions on Smart Grid, 2020.

[6] B. Nordman and K. Christensen, "Local power distribution with nanogrids," in 2013 International green computing conference proceedings. Ieee, 2013, pp. 1–8.

[7] M. Ban, M. Shahidehpour, J. Yu, and Z. Li, “A cyber-physical energy management system for optimal sizing and operation of networked nanogrids with battery swapping stations,” IEEE Transactions on Sustainable Energy, vol. 10, no. 1, pp. 491–502, 2017.

[8] H. Lotfi and v. Khodaei, Amin, “Ac versus dc microgrid planning,” IEEE Transactions on Smart Grid, vol. 8, no. 1, pp. 296–304, 2015.

[9] H. Lotfi and A. Khodaei, “Hybrid AC/DC microgrid planning,” Energy, vol. 118, pp. 37–46, 2017.

[10] R. P. Chandrasena, F. Shahnia, A. Ghosh, and S. Rajakaruna, “Operation and control of a hybrid ac-dc nanogrid for future community houses,” in 2014 Australasian Universities Power Engineering Conference (AUPEC). IEEE, 2014, pp. 1–6.

[11] S. Senemar, M. Rastegar, M. Dabbaghjamanesh, and N. D. Hatziargyriou, “Dynamic structural sizing of residential energy hubs,” IEEE Transactions on Sustainable Energy, 2019.

[12] N. Liu, X. Yu, W. Fan, C. Hu, T. Rui, Q. Chen, and J. Zhang, “Online energy sharing for nanogrid clusters: A lyapunov optimization approach,” IEEE Transactions on Smart Grid, vol. 9, no. 5, pp. 4624–4636, 2017.

[13] S. Teleke, L. Oehlerking, and M. Hong, “Nanogrids with energy storage for future electricity grids,” in 2014 IEEE PES T&D Conference and Exposition. IEEE, 2014, pp. 1–5.

[14] M. Heidari, T. Niknam, M. Zare, and S. Niknam, “Integrated battery model in cost-effective operation and load management of grid-connected smart nano-grid,” IET Renewable Power Generation, vol. 13, no. 7, pp. 1123–1131, 2019.

[15] M. R. Sandgani and S. Sirouspour, “Energy management in a network of grid-connected microgrids/nanogrids using compromise programming,” IEEE Transactions on Smart Grid, vol. 9, no. 3, pp. 2180–2191, 2016.

[16] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, “A stochastic multi-objective framework for optimal scheduling of energy storage systems in microgrids,” IEEE Transactions on Smart Grid, vol. 8, no. 1, pp. 117–127, 2016.

[17] N. B. Arias, A. Tabares, J. F. Franco, M. Lavorato, and R. Romero, “Robust joint expansion planning of electrical distribution systems and ev charging stations,” IEEE Transactions on Sustainable Energy, vol. 9, no. 2, pp. 884–894, 2017.

[18] S. Sheng, P. Li, C.-T. Tsu, and B. Lehman, “Optimal power flow management in a photovoltaic nanogrid with batteries,” in 2015 IEEE Energy Conversion Congress and Exposition (ECCE). IEEE, 2015, pp. 4222–4228.

[19] Solar home electricity data. (2014) Ausgrid. [Online]. Available: https://www.ausgrid.com.au/Industry/Our-Research/Data-to share/ Solar-home-electricity-data

[20] Electric cars available in Australia. (2019) canstarblue. [Online]. Available: https://www.canstarblue.com.au/vehicles/ electric-cars-available-australia/

[21] Journey to work in Australia. (2016) Abs beta. [Online]. Available: https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by

[22] Distributed Generation Renewable Energy Estimate of Costs. (2019) Transforming energy. [Online]. Available: https://www.nrel.gov/analysis/ tech lcoe re cost est.html,

[23] S. Schoenung, “Energy storage systems cost update,” SAND2011-2730, vol. 606, 2011.

[24] List of Converters Prices. (2019) Alibaba. [Online]. Available: https://www.alibaba.com/trade/search?fsb=y&IndexArea=product en&CatId=&SearchText=converters

[25] Converters. (2019) Amazon. [Online]. Available: https://www.amazon. com/s?k=converter&ref=nb sb noss

NOMENCLATURE

The symbols used in this paper are listed and defined in this section.

Sets	
n	Set of ENGs
t	Set of hours per day
d	Set of days per year
y	Set of years of horizon planning
i	Set of DERs
T_{in}	Set of hours that EVs are at ENG
T_{out}	Set of hours that EVs are out of ENG
Parameters	

CR	Investment cost of DERs [$/KW]
CS	Investment cost of BES [$/KWh]
CRE	Investment cost of rectifiers [$/KW]
CC	Investment cost of converters [$/KW]
CI	Investment cost of inverters [$/KW]
CB	Investment cost of bidirectional converter [$/KW]
CT	Investment cost of transformers [$/KW]
l	Rate of DC load to total load at ENG [%]
L^{max}	Pick of load at ENG [KW]
L	Load of ENGs [KW]
α	Rate of critical load to total load at ENG [%]
P_g^{max}/P_g^{min}	Maximum and minimum power purchased from the grid [KW]
P_s^{max}/P_s^{min}	Maximum and minimum power sold to the grid [KW]
C^p/C^s	Price of power purchased from and sold to the grid [$]
B	Large positive constant
M^w/M^p	Maintenance cost of wind and photovoltaic generation systems per unit [$/KW]
Q	Efficiency of all converters [%]
β	Efficiency of generation for DERs [%]
γ	Coefficient of sunlight intensity for PV systems [%]
$P_{ch}^{max}/P_{dis}^{max}$	Upper limit for charge and discharge power at BES [KW]
$P_{ch}^{min}/P_{dis}^{min}$	Lower limit for charge and discharge power at BES [KW]
$P_{ch,ev}^{max}$	Upper limit for charge power at EV's parking [KW]
$P_{dis,ev}^{max}$	Upper limit for discharge power at EV's parking [KW]
$P_{ch,ev}^{min}$	Lower limit for charge power at EV's parking [KW]
$P_{dis,ev}^{min}$	Lower limit for discharge power at EV's parking [KW]
$P_{ev,out}^{dis}$	Discharge power per KM when EVs are out of ENG [KW]
$U_s(0)$	Initial available energy at BES [KWh]
$U_{ev}(0)$	Initial available energy at EV's parking [KWh]
$\Delta U_s/\Delta U_{ev}$	Small off-set energy to avoid end-of-horizon effect at BES and EV's parking [KWh]
P^{max}/P^{min}	Upper and lower limit for the capacity of DERs [KW]
E_s^{max}/E_s^{min}	Upper and lower limit for the capacity of BES [KWh]
$U_{ev}^{max}/U_{ev}^{min}$	Upper and lower limit for energy at EV's parking [KWh]
N	Total number of EVs at a ENG
D	Average distance of movement each EV traverses a day [Km]
T_l	Time that EVs leave ENG [hr]
λ	Discharge rate of EVs per Km
r	Discount rate
k	Coefficient of net present value
z/Z	Coefficient of upper and lower energy limit for BES
Variables	
IC	Total investment cost [$]
OC	Total operation cost [$]
MC	Total maintenance cost [$]

P	DERs' installed capacity at ENGs [KW]
E	Installed capacity of SS at ENGs [KWh]
A	Binary variable represents ENG state(0 if ac,1 if dc)
P_g	Power flows from grid to ENG [KW]
P_c	Power flows from ENG to grid [KW]
P_p/P_w	PV and wind power generation at ENG [KW]
P_s^{ch}/P_s^{dis}	Charge and discharge power of BES [KW]
P_{ev}^{ch}/P_{ev}^{dis}	Charge and discharge power of EVs [KW]
I_s^{ch}/I_s^{dis}	Binary variable shows charge and discharge status of BES
I_{ev}^{ch}/I_{ev}^{dis}	Binary variable shows charge and discharge status of EVs
e_s/e_{ev}	Available energy at SS and EVs' parking [KWh]
e_s^{max}/e_s^{min}	Upper and lower limit for available energy at BES [KWh]
I_g/I_c	Binary variable shows status of energy purchasing from and selling to the grid
I_R	Binary variable shows the existence of DERs

Symbols and Abbreviations

ENG	Energy Nano-Grid
BES	Battery energy storage
DER	Distributed energy source
EV	Electrical vehicle
EM	Energy management
PV	Photovoltaic