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Load Demand, Batteries, and Electric Vehicles Modelling to the Energy Management of Microgrids

Daniel Tenfen^{*(a)}, Benoit Delinchant^(b), Frédéric Wurtz^(b), Erlon C. Finardi^(a),
Jaqueline Rolim^(a), Rubiapiara C. Fernandes^(c)

^aUFSC, Campus Universitário - CTC, Florianópolis - CEP: 88040-900, Brazil

^bUniv. Grenoble Alpes, G2Elab, F-38000 Grenoble, France

^cIFSC, Av. Mauro Ramos, 950 - Florianópolis, CEP 88020-300, Brasil

Abstract

This paper presents a mathematical model for load demand, batteries and the electrical vehicles to the Energy Management (EM) problem of a Microgrid (MG) by means of a deterministic Mixed Integer Linear Programming (MILP) approach. In the EM problem, the objective is to determine a generation and consumption policy that minimises, over a planning horizon, the operation cost subject to economic and technical constraints. We propose a detail modelling of critical, curtailable (also called shedable) and reschedulable (also called shiftable) load demands and Li-ion batteries, which could be also used to represent plug-in electrical vehicles (PHEV or V2G) and are important aspects in the MG concept. To analyse the proposed modelling, a didactic MG is used, connected to the main grid, although, the proposed models could also be used in the island operation. The results indicate that the models are adequate for the MG EM, analyses of the impacts and energies polices.

Keywords: load demand; batteries; electrical vehicles; energy management; microgrids; mixed linear integer programming

1. Glossary

Index / Sets			
c	index related to CLDs ($c=1, \dots, C$);	E^D	error associated with the demand forecasted (%);
d	index related to RLDs ($d=1, \dots, D$);	EDD_{d2}^{total}	total amount of energy for the RLD $d2$ (kWh);
e	index related to batteries ($e=1, \dots, E$);	E^{PV}	forecasted photovoltaic generation error (%);
g	index related to DLDs ($g=1, \dots, G$);	E^{PW}	error associated with the wind generation (%);
t	notation for the time step ($t=1, \dots, ND$);	FDD_{d1}	final stage where the load RLD $d1$ is supplied;
Variables		H	planning horizon (h);
deb_{et}	battery e deviation of the energy from the set point in t (kWh);	IDD_{d1}	initial stage where the RLD $d1$ could be turned on;
dld_{gt}	DLD g shed or increased in stage t (kW);	$IDLD_g$	minimum time between the DLD g shed (max ($FDDL_g, SDL1_g + SDL2_g$));
eb_{et}	battery e energy in stage t (kWh);	NC_c^{max}	maximum number of stages of load shedding for CLD c ;
pbc_{et}	battery e charge power in stage t (kW);	ND	horizon number of discretizations;
pbd_{et}	battery e discharge power in stage t (kW);	NDC_c^{st}	maximum number of load shedding for CLD c ;
pd_{ct}	power of CLD c (kW) in stage t ;	OFF_c	minimum down time for CLD c after turned off;
pdc_{ct}	power of CLD c (kW) in stage t ;	On_c	minimum up time for CLD c after be turned on.
pdd_{d1t}	RLD $d1$ in stage t (kW);	PB_e^L	battery e power loss in stage t (kW);
pde_t	system deficit in stage t (kW);	PDD_{d2}^{max}	maximum power for the RLD $d2$ (kW);
pde_t	deficit during stage t (kW);	PDD_{d2}^{min}	minimum power for the RLD $d2$ (kW);

*tenfendaniel@gmail.com

pex_t	excess generation during stage t (kW);	PDD_{id}	forecast RLD d in stage i (kW);
pgb_t	power purchase in stage t (kW);	PGB_t^{max}	grid maximum power purchase in step t (kW);
pgs_t	power sell to the grid in stage t (kW);	PGB_t^{min}	grid minimum power purchase in step t (kW);
rb_{et}	battery e power reserve in stage t (kW);	PGS_t^{max}	grid maximum power sell in step t (kW);
ub_{et}	binary variable for charging ($ub_{et} = 1$) in stage t ;	PGS_t^{min}	grid minimum power sell in step t (kW);
$ub_{et}^{aux1/2}$	auxiliary binaries variables to set the status of current (1) or voltage (2) constant in charge mode at stage t ;	PV_t	forecast photovoltaic power in step t (kW);
uc_{ct}	binary variable that indicates whether CLD c is on ($uc_{ct} = 1$) or off ($uc_{ct} = 0$) in stage t ;	PW_t	forecast wind electrical power in step t (kW);
ud_{dl}	binary variable that indicates whether RLD d starts ($ud_{dl} = 1$) in stage t ;	RB	necessary number of stages for the reserve;
udg_{gt}	binary variable that indicates whether DLD g starts ($udg_{gt} = 1$) in stage t ;	$SDLI_g$	number of stages in which DLD g is off;
ug_t	binary variable that indicates whether the MG is importing energy ($ug_t = 1$) in stage t ;	$SDL2_g$	number of stages for recovers the DLD g shed;
yc_{ct}	auxiliary binary variable for indicating the end of the load shedding in stage t of CLD c ;	SP_t	energy sell price in stage t (R\$/kWh);
zc_{ct}	auxiliary binary variable for indicating the start of the load shedding in stage t of CLD c ;	UDD_{dl}	number of stages in which RLD d is on;
Parameters		$VDLI_g$	vector with [-1] times the number of stages in which DLD g is off;
BP_t	energy purchase price in stage t (R\$/kWh);	$VDL2_g$	vector with [%] of the load shift sum in each time where DLD g need to recover;
$CB1_e$	battery e constant power in constant voltage mode (kW);	α_e	$SDLI_g$
CB_e	battery e maximum charge power in constant current mode (kW);	η_e^{bc}	battery e charge efficiency;
CC_c	incremental cost during one hour of load shedding (R\$/kW) of CLD c ;	η_e^{bd}	battery e discharge efficiency.
CD	load deficit incremental cost (R\$/kWh);	Abbreviations	
CDB_e	battery e cost due to the deviation of the energy from the set point in t (R\$/kWh);	CLD	Curtable Load Demand
CE	system excess energy incremental cost (R\$/kWh);	DER	Distribution Energy Resource
DB_e	battery e maximum discharge power (kW);	DLD	Diffuse Load Demand
DC_{ct}	forecast CLD c in stage t (kW);	EM	Energy Management
DLD_g^{max}	maximum numbers of sheds for the DLD g ;	ESS	Energy Storage System
D_t	forecast critical load demand in stage t (kW);	MG	Microgrids
D_t^F	forecast critical load demand power in step t ;	PHEV	Plug in Electrical Vehicle
EB_e^F	battery e final energy (kWh);	PLD	Pre-diffuse Load Demand
EB_e^I	battery e initial energy (kWh);	RLD	Reschedulable Load Demand
EB_e^{max}	maximum energy for battery e (kWh);	SOC	State of Charge
EB_e^{min}	minimum energy for battery e (kWh);	SOH	State of Heal
EB_e^{st}	battery e energy set point (kWh);	V2G	Vehicle to Grid

2. Introduction

The integration of controllable load demands, energy storage systems, small renewable generators, electrical vehicles in modern electrical energy grid is a trend that is currently in progress. The presence of these Distribution Energy Resources (DERs) and controllable loads can reduce fossil fuel consumption, load peak shaving, as well as postpone investments in new transmission and distribution lines [1,2]. In this new paradigm, it is important to highlight the Microgrids (MGs), which are emerging as an additional element to maintain the growth and sustainability of the modern electric energy industry. Roughly speaking, a MG consists of a group of DERs and controllable and uncontrollable loads that might operate in a controlled, coordinated way either while connected or in island operation.

A methodological challenge that supports the operations issues of MGs is the Energy Management (EM) problem [3,4]. In general, solving this problem requires determining a generation and a controllable load demand policy that minimizes, over a planning horizon, an objective function subject to economic and technical constraints. The generation policy is given by the on/off status, the respective output active power of each controllable DER, the on/off status of the Curtable Load Demand (CLD, also called shedable) and the schedule of the Reschedulable Load Demand (RLD, also called shiftable). This policy is used as reference for the voltage and frequency control in MG real-time operation. Because it is necessary to minimize an objective function subject to constraints, the EM is usually performed based on the solution of an optimization problem [5].

Concerning load demand, it can be classified by priority and type as critical, CLD and RLD [6]. The RLD has a particular characteristic of being able to be allocated across a range of time. The CLD may

have the power supply cut, as a non-priority load, if necessary. The critical load demand has to be full supplied all the time, otherwise, it will cause deficit in the system. Regarding the batteries, the most ascending technology nowadays are the lithium-ion batteries, used in electric cars, mobile phones, notebooks, being the focus of this paper.

In this paper, the EM is obtained by solving a deterministic mixed-integer linear programming problem, where the planning horizon is 24 hours with one-minute time steps. This paper is organized as follows: in the next section, we detail the load demand, the lithium-ion battery and the electrical vehicles modelling; then, in Section 4, we present the didactical MG, the optimization model related to the EM problem and some computational experiments; finally, Section 5 provides the primary conclusions of this paper.

3. Load Demand, Batteries and Electrical Vehicle Modeling

3.1. Load Demand

As aforementioned, a MG may contain different load demands: critical, CLD and RLD. Naturally, the critical load is the most important, and the impossibility of supplying this type of demand is modelled as a deficit (expensive fictitious generator). We model the CLD using an on/off approach because these loads are usually controlled by a switch and the cost of shed a load is linked to the marginal cost. The CLD modelling is given by:

$$CC_{ct} \cdot pdc_{ct}, \quad (1)$$

$$-pdc_{ct} - uc_{ct} \cdot DC_{ct} \leq -DC_{ct}, \quad (2)$$

$$pde_t + uc_{ct} \cdot \left[D_t + \sum_{c=1}^C (DC_{ct}) + \sum_{d=1}^D (\max(PDD_{id})) \right] \leq D_t + \sum_{c=1}^C DC_{ct} + \sum_{d=1}^D (\max(PDD_{id})), \quad (3)$$

$$uc_{c,t-1} - uc_{ct} + zc_{ct} \leq 0, \quad (4)$$

$$-uc_{c,t-1} + uc_{ct} + yc_{ct} \leq 0, \quad (5)$$

$$\sum_{t=1}^{ND} zc_{ct} \leq NDC_c^{st}, \quad (6)$$

$$-\sum_{t=1}^{ND} uc_{ct} \leq -ND + NC_c^{\max}, \quad (7)$$

$$\sum_{i=1}^{OFF_c} zc_{c,t-1+i} \leq 1, \quad (8)$$

$$\sum_{i=1}^{ON_c} yc_{c,t-1+i} \leq 1 \quad (9)$$

$$0 \leq pdc_{ct} \leq DC_{ct}, \quad (10)$$

$$uc_{ct}, yc_{ct}, zc_{ct} \in \{0,1\}, \quad (11)$$

Equation (1) is the cost due to the discontinuity. This cost is related to the marginal cost of each step time and could also be used different values for different step time. Equation (2) is used to set DC_{ct} to pdc_{ct} when uc_{ct} is off (relate to the cost), while (3)¹ is used to prevent the deficit before any load demand shed in any situation. Equation (4) is the logical equation to the change of status of the load c (1-on to 0-off) while equation (5) is the logical equation to the change of status (0-off to 1-on). Equation (6) and (7) are the maximum frequency of discontinuity and the maximum time of discontinuity, respectively. Equations (9) and (10) are the limits of down and up time, respectively after the load be turned off or on. The maximum/minimum load demand cut and the associated binary variables are given by (10) and (11),

¹ The sum within the brackets, which is multiplied by uc_{ct} , and in the right side of the (3) is just to guarantee that it will a big number, although it could be used a bigger value.

respectively.

Note that if the respective CLD c do not have a minimum up time after the shedding the equations (5) and (9) do not need be used. The same is for the minimum down time with the equation (8), although the equation (4) needs to be used due to the maximum frequency.

If the approach for CLD model is with just continuous variables, allowing the control of the load power, just (1) is need, also including pdc_{ct} in (39) and removing uc_{ct}, DC_{ct} .

The RLD has a particular characteristic of being able to be allocated across a range of time. The economic benefit of this load could be measured with the normal load at time of use and the new schedule time of use. In the next equations, we present the modelling for each RLD d , non-interruptible, using binary variables approach:

$$\sum_{i=1}^{UDD_{d1}} PDD_{d1i} \cdot ud_{d1,t-i+1} - pdd_{d1t} = 0 \text{ for } IDD_{d1} \leq t \leq FDD_{d1}, \quad (12)$$

$$pdd_{d1t} = 0 \text{ for } FDD_{d1} < t < IDD_{d1}, \quad (13)$$

$$\sum_{t=IDD_{d1}}^{FDD_{d1}-UDD_{d1}} ud_{d1t} = 1, \quad (14)$$

$$ud_{d1t} \in \{0,1\}, \quad (15)$$

Equation (12) is the constraint to set the PDD_{di} to pdd_{dt} considering the binary variable ud_{dt} of the start. Equation (13) is to set zero to pdd_{dt} outside the range of RLD d . Meanwhile, (14) ensures that the load demand will be turned on only once, and (15) is the associated binary variable. Equations (13) and (14) are important due the excess of intermittent generation in some step times, not giving a correct answer to the system when there are more energy than necessary.

The equations above are used when the RLD is not interruptible, using binary variables and knowing the load behavior as presented in Figure 1 (a). If the RLD could be interruptible, keeping the same sequence of PDD_{di} the load could be divided in N intervals of not interruptible D RLD, as presented in Figure 1 (a). The sequence for these respective variables could be set as constraints.

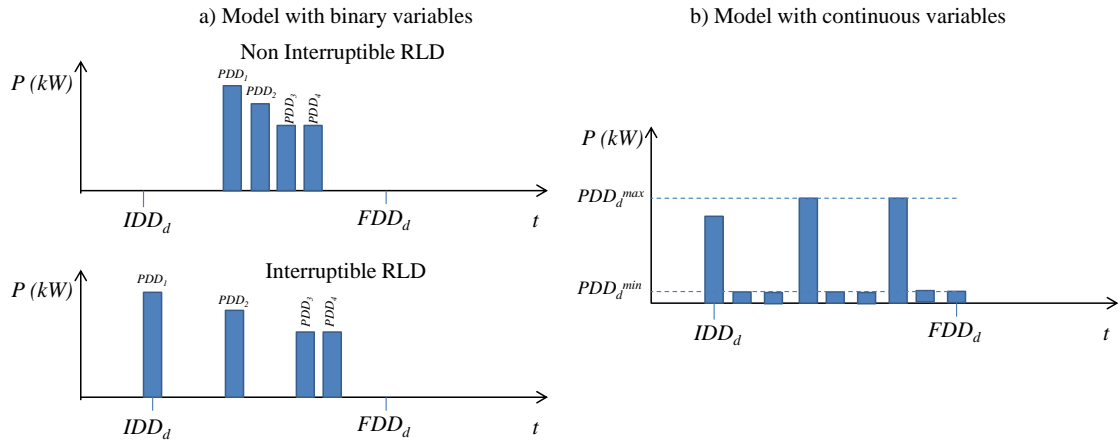


Figure 1: Example of RLD with the discrete and continuous modelling approach.

For some RLD models the use of just continuous variables is acceptable, controlling the power in each stage. The Figure 1 (b) presents an example for this load and the modelling is presented in the next equations:

$$\sum_{t=IDD_{d2}}^{FDD_{d2}} pdd_{d2t} \cdot H / ND = EDD_{d2}^{total} \quad (16)$$

$$pdd_{d2t} = 0 \text{ for } FDD_{d2} < t < IDD_{d2}, \quad (17)$$

$$PDD_{d2}^{\min} \leq pdd_{d2t} \leq PDD_{d2}^{\max} \text{ for } FDD_{d2} > t > IDD_{d2}, \quad (18)$$

Equation (16) is to guarantee that the total energy demand will be supplied, while (17) and (18) are to set the interval and the maximum and minimum power.

There are electrical loads demands which are used for thermals purposes (heating/cooling), following a specified comfort temperature. In some loads a control to track the temperature is performed. These control characteristic of follow a temperature range could not be interesting to the EM, mostly because it is not linked to the optimization modelling including the power/time of use. To deal with the problem some authors use these loads as controllable loads in the EM, including the power behavior and the limits of temperature in the problem, as presented in [7]. For each of these loads various peculiarities have to be considered, because the systems for heating or cooling a specific environment/equipment will have their particularly characteristics in the modelling.

For the modelling of an electrical load demand for thermal purpose, in this paper, we will use the diffuse approach [8] and assume: the electrical load demand is known for each step time; the load could be turned off for a specific number of step times if a previous/posterior known increment (%) of the load is performed without trespassing the temperature limits, as presented in Figure 2. The previous increment of the load demand we will call thermal Pre-diffuse Load Demand (PLD) and the thermal posterior Diffuse Load Demand (DLD).

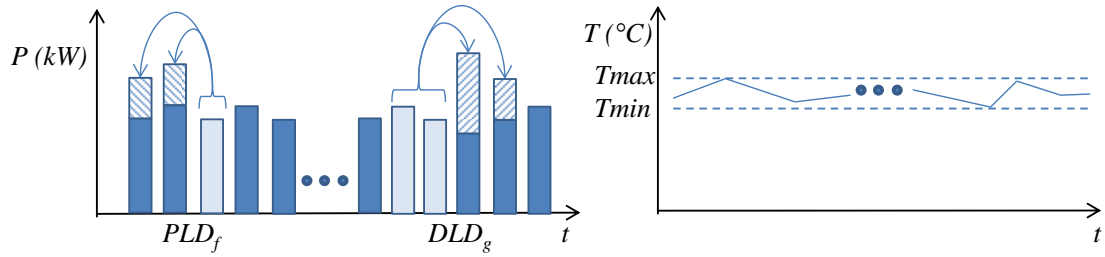


Figure 2: Example of PLD and DLD modelling.

The modelling for the DLD is given by:

$$\sum_{i=1}^{SDL1_g} VDL1_{gi} \cdot DLD_{gi} \cdot udg_{g,t-i+1} + \sum_{j=1+SDL1_g}^{SDL1_g+SDL2_g} VDL2_{gj} \cdot \sum_{i=1}^{SDL1_g} DLD_{gi} \cdot udg_{g,t-j+1} - dld_{gt} = 0, \quad (19)$$

$$\sum_{t=1}^{ND} udg_{gt} \leq DLD_g^{\max}, \quad (20)$$

$$udg_{gt} \cdot 0.1 \leq DLD_{g,t+SDL1_g+SDL2_g}, \quad (21)$$

$$\sum_{i=1}^{IDL_g^{\max}} udg_{g,t+i-1} \leq 1, \quad (22)$$

$$udg_{gt} \in \{0,1\} \quad (23)$$

Equation (19) is the constraint to set the $DLD_{g,ij}$ to dld_{gt} considering the binary variable udg_{gt} of the start. Equation (20) is to set the maximum number of times that is possible the use of these load, while (21) is to prevent one load shed in the end of the load supply, before the possibility of recover. The equation (22) is to set a minimum amount of time between the sheds, while (23) is the binary constraint.

Note that the DLD and PLD have almost the same behavior in the modelling, just with slight adjustments in the previous equations ($t-i+1$ to $t+i$, $t-j+1$ to $t+i$, $t+SDL1+SDL2$ to $t-SFL1-SFL2$ in the indices and the parameters names), and due to this reason, it is not necessary to rewrite.

3.2. Batteries

The Energy Storage Systems (ESSs) are important for the MG, especially due to: intermittent

characteristics of the renewable generation and load demand; reserve of the system; and for the island operation of the MG. Consequently, the presence of ESSs in a MG might also increase significantly the quality and reliability of energy supply. The most common ESSs are electrical, mechanical, thermal, or chemical, as batteries, supercapacitors, flywheels, compressed air, superconducting magnetic energy storage and water pumping.

Regarding the general ESS modelling, for the costs and constraints on the problem of a MG EM, some basic information is needed such as:

- Cost of use: the life expectancy of ESSs could be linked to the number of cycles of the same, and depending on their technology, this consideration is necessary.
- Capacity: refers to the energy that can be accumulated in the ESS;
- Maximum power charge and discharge;
- Efficiency: this will represent a loss in power cycles of charging and discharging of the ESS;
- Self-discharge: ESS may have a decrease in the amount of energy storage over time, even without its use.

Even for the same type of ESS several characteristics in the modelling are different depending on the size and technology employed, as presented in [9] for the chemical batteries.

As we described before, we are interested in the modelling of the Li-ion batteries, which are increasing in presence in recent years. The classification types of Li-ion batteries there are: Lithium Cobalt Oxide; Lithium Manganese Oxide; Lithium Iron Phosphate; Lithium Nickel Manganese Cobalt Oxide; Lithium Nickel Cobalt Aluminium Oxide ; Lithium Titanate; and others [10]. Each of these Li-ion batteries have particularities for a specific use, although, we are modelling in a generic way. Some of the peculiarities are related with the charge and discharge operation.

In [11] is proposed a cost function for the battery use (due to the degradation of the State of Heal - SOH). It is proposed a quadratic cost function for the deviation of the State of Charge (SOC) from a set point and the energy charge in one time step time. The cost of discharging is considered null while the cost of charge is also quadratic. In the formulation proposed in this paper we will penalise the charge and the deviation of the SOC set point empirically with linear function. The deviation from the specific SOC was approximate by the following linear equations:

$$CDB_e \cdot deb_{et}, \quad (24)$$

$$eb_{et} - deb_{et} \leq EB_e^{st}, \quad (25)$$

$$-eb_{et} - deb_{et} \leq EB_e^{st}, \quad (26)$$

The quadratic depreciation cost due to the charge was approximate from [11] with a convex piecewise linear technique, with 4 linear functions, as described in [12].

The charges and discharges will influence the SOH and also are linked to the SOC of the batteries [10]. For discharge characteristics are highlighted: the performance decreases with cold temperature and increases with heat; heat shortens battery life; cannot over-discharging; deploy a larger battery if repetitive deep discharge cycles cause stress; moderate DC discharge is better for a battery than pulse and aggregated loads. As for charge: Li-ion cannot accept overcharge; the charge is between 0.5 and 1C in stage of constant current; Li-ion does not need to be fully charged and avoiding it prolongs battery life. Figure 3 presents an approximation of the charge characteristics in constant current and constant voltage, depending on the SOC [13].

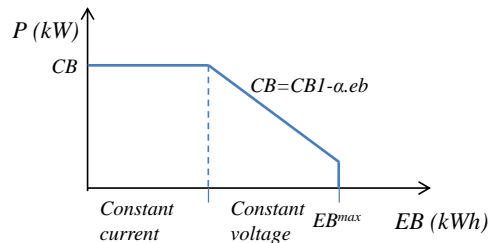


Figure 3: Li-ion charge characteristics.

The efficiency is very high for the charge and discharge and the self-discharge is very low for this battery technology. The temperature influence is negligible in this paper due to the constant temperature

assumption.

The others characteristics are modelling as constraints equations:

$$eb_{e,t+1} - eb_{et} + \left(\frac{pbd_{et}}{\eta_e^{bd}} - \eta_e^{bc} \cdot pbc_{et} \right) \cdot \frac{H}{ND} = -PB_e^L \cdot \frac{H}{ND}, \quad \text{para } t=2, \dots, ND-1, \quad (27)$$

$$eb_{e2} + \left(\frac{pbd_{e1}}{\eta_e^{bd}} - \eta_e^{bc} \cdot pbc_{e1} \right) \cdot \frac{H}{ND} = -PB_e^L \cdot \frac{H}{ND} + EB_e^I, \quad (28)$$

$$eb_{eND} - \left(\frac{pbd_{eND}}{\eta_e^{bd}} - \eta_e^{bc} \cdot pbc_{eND} \right) \cdot \frac{H}{ND} = PB_e^L \cdot \frac{H}{ND} + EB_e^F, \quad (29)$$

$$-eb_{et} + \sum_{i=1}^{RB} \frac{rb_{e,t+i}}{\eta_e^{bd}} \cdot \frac{H}{ND} \leq -EB_e^{\min}, \quad eb_{et} \leq EB_e^{\max}, \quad (30)$$

$$0 \leq pbc_{et} \leq CB_e, \quad 0 \leq pbc_{et} \leq CB1_e - eb_{et} \cdot \alpha_e, \quad (31)$$

$$0 \leq pbd_{et} \leq DB_e, \quad 0 \leq rb_{et} \leq DB_e, \quad (32)$$

$$pbc_{et} - ub_{et} \cdot CB_e \leq 0, \quad (33)$$

$$ub_{et} \cdot DB_e + pbd_{et} \leq DB_e, \quad (34)$$

$$ub_{et} \in \{0,1\}, \quad (35)$$

The constraint (27) is the energy balance of the battery throughout each stage. The initial and final energy for the battery e is defined by the constraints (28) and (29), respectively. The constraint of minimum and maximum battery energy is given by (30). Ramps for the battery charge are given by (31) and (32) for the discharge. We note that the reserve battery is the sum of the discharge for maximum power ramp, or in case you are not discharging during stage t , is the maximum power discharge itself. Constraints (33), (34) and (35) are used to prevent the battery charge and discharge on the same stage t (a situation that can occur when there is excess intermittent generation).

If is not possible control the charge power (i.e. when the control is not accessible and it is made by a switch on/off) the following equations are included:

$$-pbc_{et} + ub_{et}^{aux1} \cdot CB_e + ub_{et} \cdot 10000 \leq 10000, \quad (36)$$

$$-pbc_{et} - \alpha_e \cdot eb_{et} + ub_{et} \cdot 10000 + ub_{et}^{aux2} \cdot CB1_e \leq 10000,$$

$$-ub_{et}^{aux1} \cdot 0.7 \cdot EB_e^{\max} + eb_{et} \leq 0.7 \cdot EB_e^{\max}, \quad -ub_{et}^{aux2} \cdot 0.7 \cdot EB_e^{\max} - eb_{et} \leq -0.7 \cdot EB_e^{\max}, \quad (37)$$

$$ub_{et}^{aux1} + ub_{et}^{aux2} = 1$$

Equations (36) are to set the minimum and the maximum charge in the same level, while (37) are the logical auxiliaries binaries variables to verify the if the SOC is in the current or voltage constant charge (considering that the battery will be in the constant voltage charge in 70% of the SOC).

3.3. Plug in Electrical Vehicles (PHEV) and Vehicles to Grid (V2G)

The electrical vehicles that could be connected to the grid are increasing and its perspective is continuous this grow. These vehicles are usually classified by the technology used: the hybrid or the fuel cell technology which could be used as a conventional controllable microgeneration; the photovoltaic vehicles which could be connect to the grid and used as a renewable generation; and the plug-in hybrid (PHEV) or the battery-powered vehicles which could be used as an ESS. The advantages/disadvantages of the two first technologies are well known since the behavior is already well known in the literature, although the third one is currently in discussion [11].

The behavior of the battery-powered vehicles connected to the grid might be different depending on the local policy adopted. Most of this vehicles use Li-ion batteries and in this paper we will considered this technology. To quantify the impact expectation is necessary first modelling. In this paper we proposed the modelling as an electrical load demand or as a battery.

If the electrical vehicles will just be charged when connected to the system they could be modelled as

² The number 10000 is just a big number to guarantee the logical, although other big number could be used.

an electrical load demand. Since the SOC is known when the vehicle is connected the charge behavior could be forecasted, even for different speed charges with different charges stations. These loads could be considered as critical load demand or a RLD as modelled previously in item 3.1. If these vehicles could be connected to the main grid as an ESS they could provide essential support for the grid when connected, as described in the beginning of item 3.2. The model will differ from the previous sections due to the time when it is connect to the grid. If the owner of the electrical vehicle is different of the owner of the local electrical system different policies have to be established for the mutual interest be in accord, representing this on the model [14].

Since the modelling proposed for the electrical vehicles will follow the modelling for critical load demand, RLD or the Li-ion battery when connected, we will not model this explicitly, due to the modelling purpose of the paper.

4. Didactical Microgrid and Computational Results

4.1. Didactical Microgrid and Complete EM Modelling

To present the results of the models proposed in the previous chapter we formulate a problem for a microgrid composed by: a 4 kW photovoltaic panel; a 7 kW wind generator; possibility of buy/sell energy from/to the grid; critical load demand; a CLD; a RLD with Binary approach (RLDB); a RLD with the Continuous approach (RLDC); a DLD; and a 30kWh Li-ion battery. The Figure 4 illustrates the system.

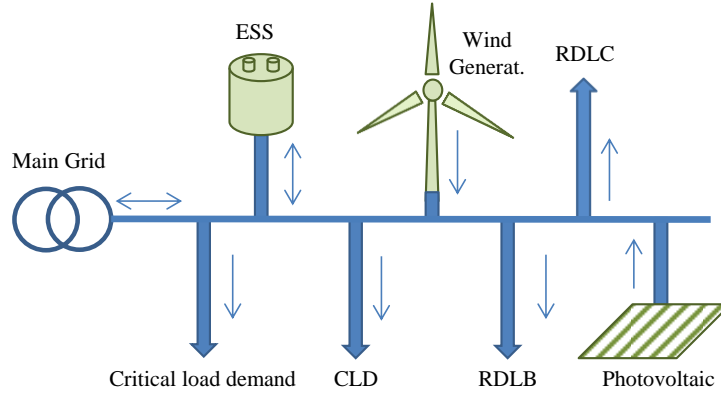


Figure 4: Didactical microgrid.

The complete model for the didactical microgrid is given by:

$$\min f = \sum_{t=1}^{ND} \left\{ \left[\sum_{c=1}^C CC_c \cdot pdc_{ct} + \sum_{e=1}^E CDB_e \cdot deb_{et} + BP_t \cdot pgb_t - SP_t \cdot pgs_t + CD \cdot pde_t + CE \cdot pex_t \right] \cdot H / ND \right\} \quad (38)$$

$$\text{s.t.:} \quad \sum_{e=1}^E (pbd_{et} - pbc_{et}) + pgb_t - pgs_t + pde_t - pex_t - \sum_{d=1}^D pdd_{dt} - \sum_{c=1}^C (uc_{ct} \cdot DC_{ct}) - \sum_{g=1}^G dld_{gt} = D_t + \sum_{g=1}^G DLC_{gt} - PV_t - PW_t \quad (39)$$

$$-\sum_{e=1}^E (rb_{et}) - pde_t \leq PV_t + PW_t - D_t - E^D \cdot D_t - E^{PV} \cdot PV_t - E^{PW} \cdot PW_t \quad (40)$$

$$PGB_t^{\min} \leq pgb_t \leq PGB_t^{\max}, \quad (41)$$

$$PGS_t^{\min} \leq pgs_t \leq PGS_t^{\max}, \quad (42)$$

$$pgb_t - ug_t \cdot PGB_t^{\max} \leq 0, \quad (43)$$

$$ug_t \cdot PGS_t^{\max} + pgs_t \leq PGS_t^{\max}, \quad (44)$$

$$ug_t \in \{0,1\}, \quad (45)$$

CLD (2)-(11),
RLDB (12)-(15),

RLDC (16)-(18),
DLD (19)-(23),
Li-ion Battery (25)-(35).

The objective function (38) is composed by CLD and batteries costs, as well as costs and profits associated with grid energy transactions and the artificial variables for deficit and excessive power generation³. Equation (39) is the energy balance constraints and (40) is the system reserve requirements. Notice in (40) the assumption that the system will prevent forecasts error and will supply at least the critical load demand, considering the for RB minutes (30). Equations (41)-(45) represent the limits of energy transactions with the grid and are used to prevent the import/export energy from/to the grid in the same step t . Note that the values for C , D , E and G are set to 1 (one) since we consider just one of these loads and batteries in the didactic microgrid.

Although the formulation consider a connected operation with the main grid, if the values of the $PGB(S)_t^{min(max)}$ are set to zero, the optimization problem then represent an island operation of the MG.

4.2. Input Data

The Figure 5a shows the forecast values for the critical load demand, CLD, RLDB and DLD and Figure 5b the energy price and the intermittent generation, where the planning horizon H is 24 hours, discretized in 1-minute time-steps (therefore, $ND = 1440$).

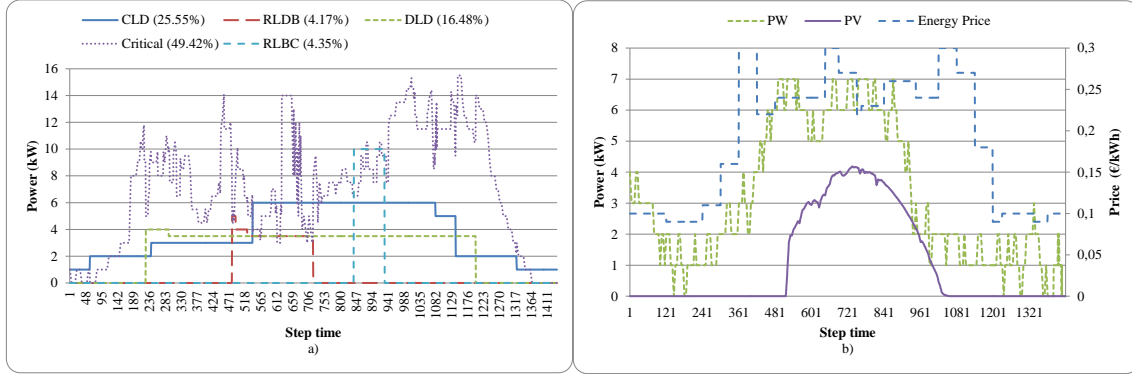


Figure 5: Loads demands, energy price and renewable generation forecasting

The maximum power grid interchange is 20 kW and the minimum is null, in all stages. The deficit incremental cost is 10 R\$/kWh and the excess generation incremental cost is 2 R\$/kWh. The forecast errors of the renewable generation are 10% and 5% for the demand. Others data are presents in Table 1.

Table 1. Battery, CLD, RLDB, RLDC and DLD data

Battery		RLDB/RLBC		CLD/DLD	
CB	18	RLDB		CLD	
CB_I	60	IDD	1	CC	0.28
α	60	FDD	1440	NC^{max}	2
DB	30	UDD	240	NDC^{st}	240
RB	10			OFF/ON	60
EB^L	0			DLD	
EB^F	12			DLD^{max}	3
EB^I	12	RLDC		$IDLD$	60
EB^{max}	30	IDD	1	$SDLD1$	15
EB^{min}	6	FDD	420	$VDLD1$	$[-1, \dots, -1]^a$
EB^{st}	12	EDD	15	$SDLD2$	8
η_{bc}	0.9	PDD^{min}	0	$VDLD2$	$[0.12, 0.12, 0.12, 0.12, 0.12, 0.05, 0.05, 0.05]$
η_{bd}	0.95	PDD^{max}	10		
CDB	$5.04e-3$				

^a with the size = $SDLD1$

³ The artificial variables of deficit and excess generation exists to the model have a solution in any situation.

Then, considering the data presented in this section, the resulting EM problem is a MILP optimization problem with 21,795 variables (14,492 continuous and 7,303 binary ones).

4.3. Computational Results

The computational model is implemented in Matlab 2011b and the tests were executed in an Intel Quadcore i7 2.80 GHz. We use the Gurobi 5.5 as the MILP solver.

To exemplify the modelling we made several tests. The Case (i) is where all the loads demand are considered as critical, importing/exporting the energy from/to the main grid, without battery. Since the system does not have a battery, no reserve is considered and it is necessary contract 30 kW to supply the load demand. The Case (ii) is where the classical generic modelling⁴ to the battery is considered [15]. The Case (iii) is where the Li-ion battery model is introduced. The Case (iv), (v), (vi) and (vii) include the different load demand modelling, now considering the loads as presented in Figure 5. The Case (viii) is to present the load modelling without the battery in the system. The cases and the results of the EM are summarized in the Table 2.

Table 2. Optimal costs and Computational time.

	Classic Battery	Li-ion Battery	DLD	RLDB	RLDC	CLC	Cost Function (€)	Comput. Time (s)	Comp Case (i)
Case (i)*	N	N	N	N	N	N	54,09	0,00	
Case (ii)	Y	N	N	N	N	N	48,68	59,06	-10,00%
Case (iii)	N	Y	N	N	N	N	50,17	19,80	-7,25%
Case (iv)	N	Y	Y	N	N	N	49,77	35,16	-7,99%
Case (v)	N	Y	Y	Y	N	N	47,49	60,08	-12,20%
Case (vi)	N	Y	Y	Y	Y	N	44,95	60,08	-16,89%
Case (vii)	N	Y	Y	Y	Y	Y	44,10	60,06	-18,47%
Case (viii)*	N	N	Y	Y	Y	Y	48,21	24,41	-10,87%

* These cases do not consider the 10min reserve due to the absence of battery

In Table 2, when the “N” appears in the table for the load demand, is that load is considered critical. The Case (i) presents the highest cost and the Case (vii) the lowest cost function, with a difference of 18,47% for these cases, although the difference could be bigger if the system reserve were not considered. Is important to notice that the Case (viii) and the Case (ii) together are correspondent to the Case (vii), although the benefit including both is higher than the benefit separately. Some cases reach the maximum time of one minute, although the error was less than 0.03% before the time convergence. In Figure 6 others results are presented.

The load DLD could provide an economy of 0.75% for the system in Case (iv) comparing to the Case (iii), although this impact could be amplified, depending on the system. The loads RLDB and RLBC, even representing just 4,17% and 4.35% of the total load, respectively, could provide an economy of 8.9% in the total cost (Case (v) and Case (vi)), been an important load for the system. The economy provide by the CLD is not always seen in the total cost because the model admits that these loads will be rewarded with the marginal cost of the shed. If the owner of the system would like to know the real economy is necessary multiply the $H \cdot ND \cdot CC_{ct} \cdot pd_{ct}$ for all step time and sum them (in Case (vii) R\$ 5.77), and it will be seen the real value of the economy (in Case (vii) 29.13%).

The difference in use for the modelling of the generic battery and the Li-ion battery could be observed also in the battery use, as presented in Figure 6a. It is possible to see that the new modelling do not have the same charge behaviour and the total amount of energy used is lower, preventing the rapid decrease of the battery SOH.

The detail of the DLD in Case (iv), showed in Figure 6b, presents exactly the formulation proposed for this load demand. It is possible to verify the behavior of the controllable loads demand in Figure 6c for the Cases (iv), (v), (vi) and (vii). Figure 6d presents the difference in the load exchange with the grid for the Case (i) and (viii) where the impact of the controllable load demand for the system could be evaluated.

⁴ The differences are in (24), (25), (26) and (31).

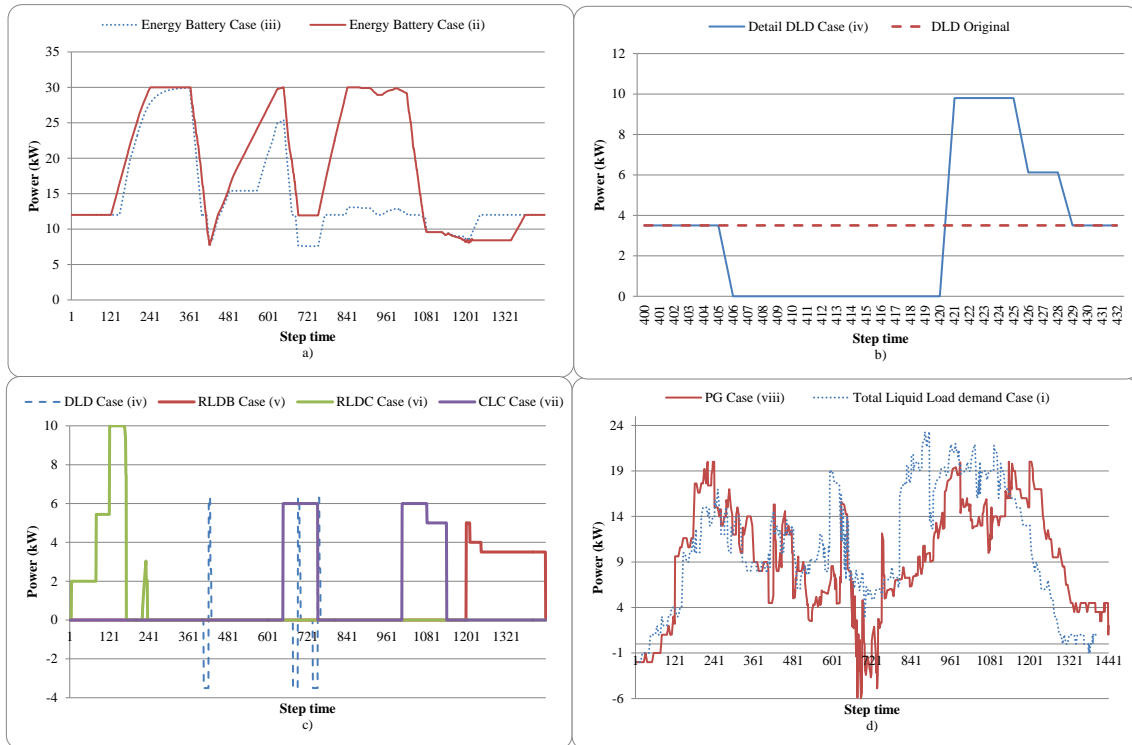


Figure 6: Cases results

5. Conclusions

The proposed modelling paper presents new models for controllable load demands and Li-ion batteries, also with a possibility of the models to be used for electrical vehicles for the microgrid EM, which proved feasible to implement. The models could be used to support the system operation, planning, policies and to quantify impacts. The results may not have demonstrated all the potential for EM economy, being necessary tests in other systems. Regarding the modelling of Li-ion batteries, this still needs more research on improving the modelling, especially due to the temperature, since they will be used in electric vehicles which are usually parked outdoors.

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