Simplifying the Data for the Optimal Sizing and Operation of PV and Storage in a Household by Linear Transformations

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***Abstract*—Optimal sizing and operation of a household with photovoltaic (PV) and storage requires a proper consideration of some uncertain parameters, as demand and PV generation. A one-year case study, including several scenarios and hourly discretization, may be very efficiently solved using an off-the-shelf solver on a laptop. However, getting those data is not always an easy task. In this work, we study whether it would be possible to get an approximate solution by using aggregate measures for those uncertain parameters and how should the problem be transformed to handle that aggregated information. By taking into account the average values of consecutive periods, we propose a linear transformation of the constraints and a set of additional ones to get this goal. Results over a case study show that the proposed procedure provides reasonable values, although the precision could be improved if some additional information, apart from the average values of the uncertain input data, is considered.**

***Index Terms*—PV and storage, household, sizing and operation, optimization, average value**

NOTATION

Parameters and sets are indicated in uppercase. Variables and indices are indicated in lowercase. Average values use the index q and have the same name as the value with index t but adding a hat, for instance $D_t \rightarrow \widehat{D}_q$, $gd_t \rightarrow \widehat{gd}_q$.

Indices and Sets

- q, Q — Index and set for average values, $q \in Q$.
- t, T — Index and set for periods of time, $t \in T$.
- T_q — Subset of T, the set of T_q is a partition of T.

Parameters

- CAB — Battery amortization cost, (€/(kWh · day)).
- $CAPV$ — PV amortization cost, (€/(kWp · day)).
- CTP — Cost of grid connection capacity, (€/(kW · day)).
- D_t — User energy demand at t, (kW).
- PEC_t — Price of energy purchased from the grid, (€/kWh).
- PEV — Price of energy sold to the grid, (€/kWh).
- PVA_t — Available PV generation at t, (kW/kWp).
- α_C/α_D — Charging / Discharging battery power factor using as base the battery storage capacity, (kW/kWh).
- Δ — Lasting of each period t, (hours).
- η_C/η_D — Charging / discharging battery efficiency, (p.u.).
- PV^{max} — Upper bound for PV capacity installed, (kWp).
- F_{pi} — Upper bound for the injection to grid, as a fraction of the grid connection capacity, cc, (p.u.).
- ϕ_q — PV generation utilization factor, (p.u.).

Variables

- pv — PV capacity installed, (kWp).
- b — Battery capacity installed, (kWh).
- cc — Connection capacity to the grid, (kW).
- gd_t — Power from grid to user demand at t, (kW).
- gb_t — Power from grid to battery at t, (kW).
- bg_t — Power from battery to grid at t, (kW).
- vg_t — Power from PV to grid at t, (kW).
- vd_t — Power from PV to user demand at t, (kW).
- vb_t — Power from PV to battery at t, (kW).
- vs_t — Available power from PV that is spilled at t, (kW).
- bd_t — Power from battery to user demand at t, (kW).
- soc_t — Energy in the battery at period t, (kWh).
- soc_0 — Energy in the battery before the first period, (kWh).

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I. INTRODUCTION

Small-scale renewable energy generation is undergoing a rapid increase nowadays, in particular household photovoltaic (PV) generation. A key issue in the deployment of household installations with PV and storage is to calculate their optimal size. This problem can be posed as an optimization model and being solved for sizes of thousands of unknowns within seconds in a regular laptop. But a practical problem arises, the data to feed the model are difficult to get (or to manage) for the people interesting in solving the problem (installers and users). For instance the values for demand, even if nowadays many users have smart meters that record the power demand every 15 minutes and save the data for the last two or three years. It would be quite useful if we could get a good approximation to the optimal solution just using a reduced number of data values straightly available and with a clear interpretation. Here we propose a first step for that.

The problem of optimal sizing and operation of PV battery residential systems has been extensively studied in the literature. Most of the publications concentrate on the economic aspect, as [1], others in the technical part, as [2], and only a few take into consideration the data resolution, as [3] and [4].

The method proposed here is related to the data resolution, but with two main differences regarding previous works.The main contributions in this work are two fold:

- On one hand, we propose a method to transform the optimization problem, based on a linear transformation of the constraints and a set of additional ones, to accommodate the optimization problem to the new low-resolution data. The usual approach in the literature is to assess the impact of data resolution on: i) systems with fixed capacities, as in [3], or ii) the optimal system size, as in [4].
- Also a method to build the low resolution data is proposed. And the resolution is adaptive and related to the problem equations.

The rest of the paper is organized as follows. The initial optimization problem, the method to build the reduced data (low resolution data), the transformation for the equations and the transformed problem are described in Section II. A case study for a small problem is presented in Section III to show how the methodology is applied. Results for the case study are discussed on Section IV. And conclusions in Section V close the paper.

II. Methodology

The aim is to get a model that uses a reduced number of data straightly available and produces a good approximation to the optimal solution. The optimal solution can be gotten from an optimization problem that uses profiles with a large number of values for the uncertain parameters. For instance, it would be useful if a demand profile for one year with a time step of 15 minutes (35040 values) could be reduced to 5 or 6 average values.

We call $M1$ to the model that uses profiles with a large number of values and that produces the optimal solution. And $M2$ is the model that uses a reduced number of average values and, hopefully, provides a good approximation to the optimal solution. Both models follow the same scheme, depicted in Fig. 1, are posed as linear optimization problems, and described in what follows.

A. $M1$: Model using a large number of values

Parameters and variables in $M1$ are defined on the domain T, they are accurate profiles with a large number of values. $M1$ is posed as a two-stage stochastic program (1)-(11). In the objective function (1) the sizing decisions are in the first stage, $CAPV{\cdot}pv+CAB{\cdot}b+CTP{\cdot}cc$, and the operation cost is in the second stage, $\sum_{t\in T}\Delta{\cdot}\big[PEC_t{\cdot}(gd_t+gb_t)-PEV{\cdot}(bg_t+vg_t)\big]$. The complete model is (variables in lower case and parameters in upper case):

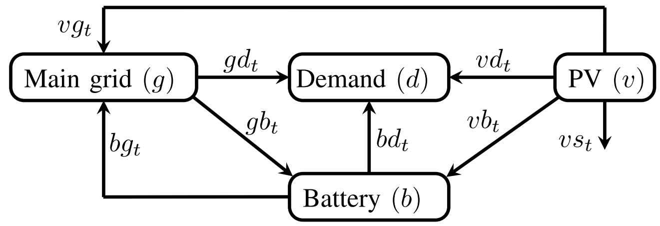


Fig. 1. System flowchart, components are boxed, and arrows stand for the power flows between components.

$$\min \Big\{CAPV\cdot pv + CAB\cdot b + CTP\cdot cc + \\ + \sum_{t\in T}\Delta\cdot\Big[PEC_t\cdot(gd_t+gb_t) - PEV\cdot(bg_t+vg_t)\Big]\Big\} \quad (1)$$

Subject to:

$$gd_t + vd_t + bd_t = D_t; \quad \forall t\in T \quad (2)$$

$$vd_t + vg_t + vs_t + vb_t = PVA_t\cdot pv; \quad \forall t\in T \quad (3)$$

$$soc_t = soc_{t-1} + \Delta\cdot\eta_C\cdot(gb_t+vb_t) \\ - \frac{\Delta}{\eta_D}\cdot(bg_t+bd_t); \quad \forall t\in T \quad (4)$$

$$soc_0 = soc_{|T|}; \quad (5)$$

$$soc_t \le b;\ t\in T \quad (6)$$

$$gb_t + vb_t \le \alpha_C\cdot b; \quad \forall t\in T \quad (7)$$

$$bg_t + bd_t \le \alpha_D\cdot b; \quad \forall t\in T \quad (8)$$

$$gd_t + gb_t \le cc; \quad \forall t\in T \quad (9)$$

$$bg_t + vg_t \le F_{pi}\cdot cc; \quad \forall t\in T \quad (10)$$

$$pv \le PV^{max}; \quad (11)$$

Where each equation stands for: (2) the demand balance; (3) the PV generation balance; (4) energy balance in the battery, being soc_0 the initial state of charge; (5) the condition to avoid the use of free energy from the battery; (6) link between the battery size and the energy it can store; upper bound for the battery charging (7) / discharging (8) power; the upper bound for connection capacity for consumption (9) / injection (10); and (11) the upper bound for the PV generation that can be installed, for instance because of the limited available room for the installation.

B. $M2$: Model using a reduced number of average values

We use the average as a measure to get the reduced values. The average is a linear transformation that can be applied to the values (variables and parameters) and the equations in $M1$ to get the corresponding equations in $M2$. Here we describe how to build $M2$ by answering two questions:

1) The average values can be interpreted as the average on a certain subset of T. T is the domain for the accurate profiles, with a large number of values. The question is how to define the subset of T for each average value.
2) How to transform the equations in $M1$ to use the average values, and if some additional equations are needed.

Given the domain $t \in T$ for the accurate profile (large number of values), we define the subsets T_q, $q \in Q$, associated with each average value with index q using these rules:

- The set of T_q with $q \in Q$ is a partition of the set T, that is: $\forall p, q \in Q$ with $p \neq q$, $T_p \cap T_q = \emptyset$, and $\cup_{q \in Q} T_q = T$.
- For each T_q, the $t \in T_q$ are consecutive, and T_{q+1} contains the consecutive periods that follow the last period in T_q. Thus the subsets T_q inherit the ordering of the periods $t \in T$, and the set of all the T_q is also an ordered set.

Variables and parameters with index t in $M1$ are vectors with T components. Each vector in T is transformed in a vector of average values in Q, index q and $|Q|$ values. This vector of average values is used in $M2$ with the same name as in $M1$ but adding a hat. The components in the two vectors are related by ($|T_q|$ is the cardinal of set T_q):

$$\widehat{\Theta}_q = \frac{1}{|T_q|} \sum_{t \in T_q} \Theta_t, \quad \forall q \in Q \tag{12}$$

For instance:

$$\widehat{D}_q = \frac{1}{|T_q|} \sum_{t \in T_q} D_t; \quad \forall q \in Q \tag{13}$$

$$\widehat{PVA}_q = \frac{1}{|T_q|} \sum_{t \in T_q} PVA_t; \quad \forall q \in Q \tag{14}$$

Variables and parameters without index t in $M1$, as for instance the capacity decisions pv, b, cc and the efficiencies η_C, η_D, have exactly the same meaning in $M1$ and $M2$. And we use the same name for them in both models (no hat).

In practice, domain T can be the hours in a year (8760 values). We explore the definition of domain Q taking into account the intervals in a Time-of-Use tariff (3-5 values) and, for each day, the intervals where: $PVA_t = 0 \; \forall t$ in the interval, and those where $PVA_t \neq 0 \; \forall t$ in the interval, (3 values).

$$\begin{aligned} T_q = \{t : PEC_t = \widehat{PEC}_q\} \text{ and } \{PVA_t = 0,\ \forall t \in T_q \\ \text{or } PVA_t \neq 0,\ \forall t \in T_q\} \end{aligned} \tag{15}$$

The condition $T_q = \{t : PEC_t = \widehat{PEC}_q\}$ allows a direct transformation of the objective function (1) in $M1$ to get the objective function (18) in $M2$. And both objective functions provide exactly the same value for the same arguments.

Ideally $M1$ and $M2$ should have the same optimal solution, or at least the same optimal values for the capacities (pv, b, cc). We apply the linear transformation (12), that defines the average values, to the equations in $M1$ to get the corresponding transformed equations in $M2$. As an example, we apply the transformation to the equation (2):

$$\frac{1}{|T_q|} \sum_{t \in |T_q|} (gd_t + vd_t + bd_t) = \frac{1}{|T_q|} \sum_{t \in T_q} D_t; \ \forall q \in Q \tag{16}$$

And we get the corresponding equation in $M2$:

$$\widehat{gd}_q + \widehat{vd}_q + \widehat{bd}_q = \widehat{D}_q; \quad \forall q \in Q \tag{17}$$

The complete version of $M1$ transformed is (18)-(29) (variables in lower case and parameters in upper case):

$$\begin{aligned} \min \Big\{ & CAPV \cdot pv + CAB \cdot b + CTP \cdot cc + \\ & + \sum_{q \in Q} |T_q| \cdot \Delta \cdot \Big[\widehat{PEC}_q \cdot (\widehat{gd}_q + \widehat{gb}_q) - PEV \cdot (\widehat{bg}_q + \widehat{vg}_q) \Big] \Big\} \end{aligned} \tag{18}$$

Subject to:

$$\widehat{gd}_q + \widehat{vd}_q + \widehat{bd}_q = \widehat{D}_q; \quad \forall q \in Q \tag{19}$$

$$\widehat{vd}_q + \widehat{vg}_q + \widehat{vs}_q + \widehat{vb}_q = \widehat{PVA}_q \cdot pv; \quad \forall q \in Q \tag{20}$$

$$\begin{aligned} \widehat{soc}_q = & (1/|T_q|) \cdot soc_0 + \Delta \cdot \eta_C \cdot (\widehat{gb}_q + \widehat{vb}_q) \\ & - (\Delta/\eta_D) \cdot (\widehat{bg}_q + \widehat{bd}_q); \quad q = 1 \end{aligned} \tag{21}$$

$$\begin{aligned} \widehat{soc}_q = & \widehat{soc}_{q-1} + \Delta \cdot \eta_C \cdot (\widehat{gb}_q + \widehat{vb}_q) \\ & - (\Delta/\eta_D) \cdot (\widehat{bg}_q + \widehat{bd}_q); \quad q > 1 \end{aligned} \tag{22}$$

$$soc_{|Q|} \geq (1/|T_{|Q|}|) \cdot soc_0; \tag{23}$$

$$\widehat{soc}_q \leq b; \quad \forall q \in Q \tag{24}$$

$$\widehat{gb}_q + \widehat{vb}_q \leq \alpha_C \cdot b; \quad \forall q \in Q \tag{25}$$

$$\widehat{bd}_q + \widehat{bg}_q \leq \alpha_D \cdot b; \quad \forall q \in Q \tag{26}$$

$$\widehat{gb}_q + \widehat{gd}_q \leq cc; \quad \forall q \in Q \tag{27}$$

$$\widehat{bg}_q + \widehat{vg}_q \leq F_{pi} \cdot cc; \quad \forall q \in Q \tag{28}$$

$$pv \leq PV^{max}; \tag{29}$$

The feasible region of (18)-(29), transformed $M1$, includes the feasible region of $M1$ and some additional points. Among these points are charging and discharging the battery at the same time. These points can be removed by adding the following constraint (derived from (25) and (26)):

$$\frac{\widehat{gb}_q + \widehat{vb}_q}{\alpha_C} + \frac{\widehat{bd}_q + \widehat{bg}_q}{\alpha_D} \leq b; \quad \forall q \in Q \tag{30}$$

Also, other additional points are related to the distribution of values inside the T_q. In particular, the amount of PV generation (vd_t) that can be used for direct self-consumption. To remove those points we add the following constraint:

$$\widehat{vd}_q \leq pv \cdot \phi_q \cdot \widehat{D}_q; \quad \forall q \in Q \tag{31}$$

Where parameter ϕ_q is a measure of correlation between demand D_t and PV generation PVA_t inside each T_q.

Thus, the complete $M2$ problem consists of equations (18)-(31). We conjecture that $M2$ could provide a good approximation of $M1$ by adding information on the extreme value inside each T_q and also some measure of the correlation between demand and PV generation for each T_q. We left those developments for future work.

III. Case Study

To illustrate the proposed methodology, $M1$ and $M2$ are applied to a toy example of small size, and the solutions from both models are compared. This toy example consists of a grid connected household with PV and storage. The time horizon is a day, and the domain T contains 24 values, t, representing

TABLE I
DEFINITION OF DOMAIN Q

<table>
<tr><td>T</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td><td>20</td><td>21</td><td>22</td><td>23</td><td>24</td></tr>
<tr><td>PEC_t</td><td colspan="13">1-13, 0.085875 €/kWh</td><td colspan="10">14-23, 0.171166 €/kWh</td><td></td></tr>
<tr><td>PVA_t</td><td colspan="6">$PVA = 0$</td><td colspan="15">7-21, $PVA \neq 0$</td><td colspan="3">$PVA = 0$</td></tr>
<tr><td>T_q</td><td colspan="6">1-6</td><td colspan="7">7-13</td><td colspan="8">14-21</td><td colspan="2">22-23</td><td>24</td></tr>
<tr><td>q</td><td colspan="6">1</td><td colspan="7">2</td><td colspan="8">3</td><td colspan="2">4</td><td>5</td></tr>
<tr><td>$\lvert T_q \rvert$</td><td colspan="6">6</td><td colspan="7">7</td><td colspan="8">8</td><td colspan="2">2</td><td>1</td></tr>
</table>

TABLE II
PARAMETERS USED IN BOTH MODELS

Parameter	Value	Units	Reference
$CAPV$	0.2488	€/(kWp · day)	[6]
$\alpha_C = \alpha_D$	0.5000	kWh/kW	[7]
$\eta_C = \eta_D$	0.9200	p.u.	[7]
F_{pi}	0.5000	p.u.	estimated
PV^{max}	15.00	kWp	estimated

the hours in a day, $\Delta = 1$ hour. A real Time-of-Use tariff [5] with three intervals is considered:

- $PEC_t = 0.085875$ (€/kWh), for $t = 1, 2, \ldots, 13$.
- $PEC_t = 0.171166$ (€/kWh), for $t = 14, 15, \ldots, 23$.
- $PEC_t = 0.085875$ (€/kWh), for $t = 24$.

For this tariff [5] the price of energy sold to the grid is $PEV = 0.051$ €/kWh, and the cost of grid connection is $CTP = 0.156794$ €/(kW · day).

Values for demand (D_t) and available PV generation (PVA_t) correspond to a household in southern Spain and are depicted in Fig. 2. According to conditions (15) we can distinguish three intervals for PVA_t: i) $t = 1, 2, \ldots, 6$ with $PVA_t = 0$, ii) $t = 7, 8, \ldots, 21$ with $PVA_t \neq 0$, and iii) $t = 22, 23, 24$ with $PVA_t = 0$.

Applying the conditions (15) to the intervals for the tariff, PEC_t, and the intervals for PVA_t we get the domain Q as a partition of T. In this case we have 5 components, $q = 1, 2, \ldots, 5$, $|Q| = 5$. This process is illustrated through the columns in Table I. The intervals for PEC_t and PVA_t, and the resulting T_q in Q are summarized in Table I. Values for parameters common to both domains are listed on Table II, and values for parameters in domain Q are provided on Table III. Also $\widehat{D}_q$ and $\widehat{PVA}_q$ are depicted on Fig. 2.

A sensitivity analysis is performed on the battery installation cost, $CAB \in [0.08, 0.16]$ €/(kWh·day). $CAB = 0.16$ €/(kWh·day) is approximately the current installation cost for a household battery in Spain (700 €/kWh, and a lifespan of 12 years). $CAB = 0.08$ €/(kWh·day) is the expected installation cost for a household battery in the next 5 to 10 years.

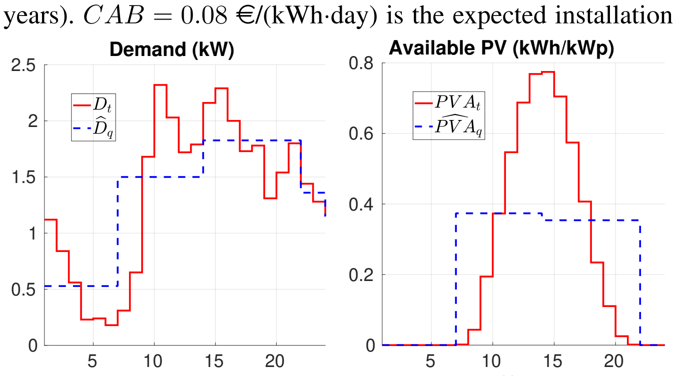


Fig. 2. Hourly profiles for: (a) Demand, and (b) Available PV generation.

TABLE III
VALUE OF PARAMETERS IN DOMAIN Q

Param. \ q →	1	2	3	4	5
t	1-6	7-13	14-21	22-23	24
ϕ_q	0.0000	0.0491	0.0491	0.0000	0.0000
$\widehat{D}_q$ (kW/h)	0.5283	1.5000	1.8262	1.3600	1.1500
$\widehat{PEC}_q$ (€/kWh)	0.0858	0.0858	0.1711	0.1711	0.0858
$\widehat{PVA}_q$ (p.u.)	0.0000	0.3736	0.3539	0.0000	0.0000

$M1$ is a linear optimization problem with 195 equations and 221 variables and $M2$ contains 53 equations and 50 variables. Both problems are solved using CPLEX under GAMS [8]. The computation time for each problem is 3.38 seconds for $M1$ and 3.23 seconds for $M2$ in a machine with Intel(R) Core(TM) i7-4510U CPU @ 2.00GHz processor and 12.0 GB RAM under Windows 10 Pro x64.

IV. DISCUSSION OF RESULTS

The focus of the discussion here is on the differences between the solutions from both models, and not in the values of the optimal solution themselves. Thus, we focus on the error in the figures, and the error (%) is calculated as:

$$\text{Error} = 100 \cdot \left(\frac{\text{Value in } M2}{\text{Value in } M1} - 1 \right) \tag{32}$$

$M1$ is always solved on T, and $M2$ is solved on Q. Just for checking purposes $M2$ is solved also on T and noted as $M2(T)$. For $M2(T)$ each T_q contains just a single t, which is $t = q$, and $q = 1, 2, \ldots, |T|$, $\phi_q = 1$. We got exactly the same results for $M1$ and $M2(T)$. This was the expected result, and shows that the additional constraints (30) and (31) in $M2$ are not distorting the problem when solved on T.

The results considered are the installed capacities (pv, battery b, and grid connection capacity cc), and the costs and incomes summarized in Table IV (all of them in (€/day)): CI cost of installed capacities, CGD cost of demand direct consumption from grid, CGB cost of battery direct consumption from grid, IBG income for injection from battery to grid, and IVG income for injection from PV to grid. The Net Cost is the value of the objective function in both models, Net Cost = $CI + CGD + CGB - IBG - IVG$.

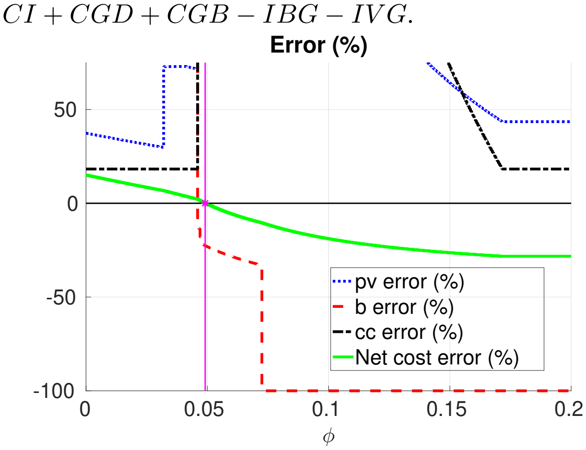
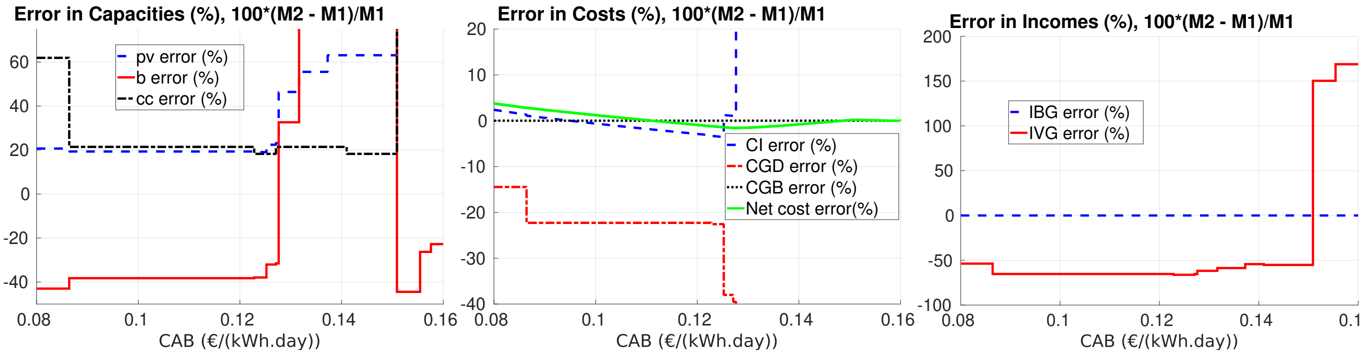


Fig. 3. Sensibility analysis on ϕ for $CAB = 0.16$ (€/(kWh·day)).



(a) (b) (c)

Fig. 4. Errors for the $M2$ results compared to $M1$ for: (a) Installed capacities pv, b, and cc, (b) Capacities cost CI, cost of demand direct consumption from grid CGD, cost of battery direct consumption from grid CGB, Net cost = $CI + CGD + CGB - IBG - IVG$, and (c) Income for injection from PV to grid IVG, income for injection from battery to grid IBG.

TABLE IV
DEFINITION OF COSTS AND INCOMES

	$M1$	$M2$
CI	$CAPV{\cdot}pv + CAB{\cdot}b + CTP{\cdot}cc$	
CGD	$\sum_{t\in T} \Delta{\cdot}PEC_t{\cdot}gd_t$	$\sum_{q\in Q} \Delta{\cdot}\widehat{PEC}_q{\cdot}\widehat{gd}_q$
CGB	$\sum_{t\in T} \Delta{\cdot}PEC_t{\cdot}gb_t$	$\sum_{q\in Q} \Delta{\cdot}\widehat{PEC}_q{\cdot}\widehat{gb}_q$
IBG	$\sum_{t\in T} \Delta{\cdot}PEV{\cdot}bg_t$	$\sum_{q\in Q} \Delta{\cdot}PEV{\cdot}\widehat{bg}_q$
IVG	$\sum_{t\in T} \Delta{\cdot}PEV{\cdot}vg_t$	$\sum_{q\in Q} \Delta{\cdot}PEV{\cdot}\widehat{vg}_q$

Parameter ϕ_q is a measure of correlation between demand and PV generation in each T_q. The value of ϕ_q can be estimated from the available data (we are working on that). Here it is fitted by using a sensitivity analysis on ϕ_q, with $\phi = \phi_2 = \phi_3$ and $\phi_1 = \phi_4 = \phi_5 = 0$. Results are shown in Fig. 3, $\phi \in [0, 1]$ but for $\phi > 0.2$ values of error remain constant. A value of $\phi = 0.04913$, as indicated on Table III, was selected because it corresponds to a zero error in net cost.

Fig. 3 shows that values of error for pv, b and cc are never zero, and their minimum value is reached for different values of ϕ. That means it is necessary to add more information to $M2$. We conjecture that information is: i) extreme values inside each T_q, and ii) a more accurate representation of the correlation between demand and PV generation.

We can see in Fig. 4a that $M2$ overestimates the value of pv and cc and underestimates the value of b. The value of cost for direct consumption from grid CGD is lower in $M2$ than in $M1$. Higher pv and lower CGD in $M2$ indicates the amount of PV self-consumption is higher in $M2$ than in $M1$. Also the value of incomes for PV generation sold to the grid, IVG, is lower in $M2$ than in $M1$, this is because PV generation is used for self-consumption instead of for injection to grid. The increase of cc in $M2$ is because it corresponds to the maximum difference between $\widehat{D}_q$ and $\widehat{PVA}_q$ instead of the difference between D_t and PVA_t. Again we think these differences could be corrected by adding the commented information.

The presented approach is still rough, as it uses only very few information (mainly average values), and despite of that the errors are usually lower than 20%.

V. CONCLUSION

This work aims at reformulating the problem of optimal sizing and operation of PV, battery and grid connection capacity in a household to get accurate solutions using low resolution data. A first approach is presented to build the low resolution data and to reformulate the problem to use those data. Reformulation is based on a linear transformation of the initial equations and the addition of some constraints.

Results over the analyzed case study show, on one hand, that the transformed problem $M2$ provides the same solution as the initial problem $M1$ when applied on the non reduced data. While, on the other hand, when the data are reduced (from 24 to only 5 in the case study), some relevant solutions in both models, as the net cost, are quite similar. But others solutions, as the optimal capacities, show a significant error.

Further research is required to identify the relevant information to be included in the reduced model. We conjecture accurate solutions could be got by adding the information on extreme values and correlations between the aggregated values. We are working on that.

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