Modeling Energy and Technology Choices in Smart Regional Energy Systems*

F. Babonneau† A. Haurie‡

1st February 2015

Abstract

This paper deals with the modeling of the long term evolution of regional energy systems in a smart city and smart grid environment. It is shown that demand response and distributed grid energy storage, driven by dynamic pricing schemes, based on locational marginal costs, can be represented in the linear programming framework of the models of the MARKAL/TIMES family. An implementation in the ETEM-SG modeling tool, which is an energy model tailored to the representation of regional energy systems is then described. An illustration is provided, based on energy scenarios concerning the Arc Lémanique region in Switzerland. Finally the SESCOM modeling framework, which is under development in a project on smart energy systems for smart cities in Qatar is introduced. This modeling approach expands ETEM-SG to the representation of useful energy demands influenced by changes in life styles, smart transmission and interconnection between regions and market price revelation at distribution levels .

1 Introduction

The aim of this paper is twofold: first, we propose and test ETEM-SG, which is a long-term energy planning model (LTEP) designed to explore the impact on regional energy system evolution of the *flexibility* introduced by demand response and grid storage technologies; second, we show how ETEM-SG will be integrated in a more encompassing approach, called SESCOM, for modeling smart energy systems in smart cities, like the ones currently in development in the Gulf region.

Demand response is defined as "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time". This corresponds to a coordinated exploitation of demand flexibility. Typically, demand flexibility exists when the energy service is associated with the integral over time of power (*i.e.* the total energy delivered) rather than with power itself. Warm water heating is a good example of flexible demand: in order for the useful demand to be met (*i.e.* temperature of warm water in a given comfort zone), the precise injection of power in the appliance needs not be specified. The only criterion is that the dynamics of power injection into the system is such that the temperature of warm water is within predefined bounds. Developments in smart grid technologies combined with the emergence

*This research has been supported by BFE/OFEN, Bern Switzerland and by Qatar National Research Fund. Christopher Andrey has been deeply involved in the development of this research when he was with ORDECSYS. In particular the application to the Arc Lémanique region owes very much to his work.

†ORDECSYS, Geneva and LEURE Laboratory, EPFL, Switzerland

‡ORDECSYS, Geneva and University of Geneva, Switzerland

of smart appliances have unveiled the possibility of using demand flexibility to relieve pressures in the energy system by adjusting the dynamics of power consumption to the energy system status.

Grid energy storage refers to the methods used to store electricity on a large scale within an electrical power grid. The development of electrical mobility, in particular Plug-in Hybrid Electrical Vehicles (PHEVs) connected through smart grids, offers new ways to store electricity in the grid. Similarly, decentralized cogeneration units and HVAC technologies can exploit heat or cold storage. Grid energy storage is a natural complement of the large scale integration of renewables in the power systems, like wind and solar technologies that are characterized by intermittency in their production.

Demand response and grid energy storage can be harnessed by sending consumers incentives to adapt their consumption pattern, the charging of electrical vehicles or the timing of power injection through cogeneration units. In a smart grid environment, the incentives take the form of a variation of the price of electricity. In order to be the most efficient at helping the integration of renewables, tariffs should vary on the same time scales as the production by renewables, *i.e.* they should be real-time tariffs. Both grid operators and utilities would be benefiting from demand-response mechanisms as they would be able to better manage their network, to balance intermittent renewable generation and to decrease investments in peaking plants by improving their assets' load factor.

The development of smart cities, like typically Masdar City in Abu Dhabi or Lusai in Qatar, will amplify the progress of smart energy systems, which will exploit smart networks in transportation and resource delivery to achieve resilience and higher efficiency. Smart energy systems foster a massive penetration of renewables as they offer new efficient ways to manage uncertainty and intermittency, congestion, transmission & distribution Interface. They also allow the "commoditization" of demand response, the introduction of new market bidding rules for storage-like flexible loads or reactive power (decentralized decisions for real/reactive energy and reserves provision). All these new features should be taken into consideration when planning for the development of energy systems at a regional or city level.

The remainder of this paper describes the modeling tool ETEM-SG that has been designed for the quantitative analysis of scenarios for the development of smart energy systems at the regional level. In Section 2 we present the simple economics of demand response induced by adaptive pricing and we justify the use of a linear program to represent it. In Section 3 we present the structure of ETEM-SG, an LTEP model including demand response and grid storage. To demonstrate the capabilities brought to ETEM-SG, a recent application to the Arc Lémanique region in Switzerland, is briefly presented in section 4. In Section 5 we refer to the ongoing research supported by Qatar National Research Fund, where ETEM-SG is integrated in a larger modeling approach, taking into consideration activities and constraints both at transmission and distribution levels. Finally Section 6 concludes.

2 The simple economics of demand flexibility

In this section we present the simple economics of demand response induced by adaptive pricing of electricity. We start with a noncooperative game model, extend it to the case of many infinitesimal agents and show that at the limit, a linear program will represent the equilibrium solution. This is an important result as it allows us to extend the linear programming framework of the usual LTEPs, like ETEM [5] or TIMES [1] to include demand response and optimal charging/storage for

PHEVs.

2.1 A noncooperative game model

In [2] the relationship between a retailer practising real-time pricing and a finite set of customers optimising the timing of their electricity consumption is modelled as a non-cooperative game which admits, under some general conditions a unique and stable Nash equilibrium. The model is summarised below, in a slightly more general formulation than the one used in [2].

Retailer The distributor has access to its own production equipment and also to the wholesale market. Depending of the total demand $D(t)$ in a time slot t of the day, the marginal cost of production is given by $\gamma(D(t))$, which is the price that will be charged.

Consumers Each consumer i has a minimum daily requirement of electricity β_j^i for each type of service j. Let $x_j^i(t)$ the demand by consumer i to satisfy service j at time slot t. The following constraints must thus be satisfied:

$$\sum_t x_j^i(t) \geq \beta_j^i, \tag{1}$$

together with:

$$x_j^i(t) \geq x_j^i[\min](t) \tag{2}$$

$$x_j^i(t) \leq x_j^i[\max](t) \tag{3}$$

where $x_j^i[\min](t)$ and $x_j^i[\max](t)$ are given bounds. The dual variables corresponding to the constraints (1) to (3) respectively are η_j^i, $\mu_j^i(t)$ and $\nu_j^i(t)$, which are greater or equal to zero. Let us define the following sets: $\underline{\mathbf{x}} = (\mathbf{x}(t))_{t\in T}$, where $\mathbf{x}(t) = (\mathbf{x}^i(t))_{i\in I}$, with $\mathbf{x}^i(t) = (x_j^i(t))_{j\in J}$.

Payoff to consumer The total demand in time slot t is given by:

$$D(t) = \sum_i \sum_j x_j^i(t). \tag{4}$$

This determines the marginal cost $\gamma(D(t))$, and hence the tariff payed at time slot t by each customer. The aim of the i-th customer is thus to minimise

$$\psi^i(\underline{\mathbf{x}}) = \sum_t \gamma(D(t)) \left(\sum_j x_j^i(t) \right), \tag{5}$$

under the constraints (1) to (3). Note that the interdependence among customers comes from the price determination equation, see (4). The Lagrangian for the i-th consumer can thus be written as:

$$
\begin{aligned}
\mathcal{L}^i &= \psi^i(\underline{\mathbf{x}}) + \sum_j \eta^i_j \left(\beta^i_j - \sum_t x^i_j(t) \right) \\
&\quad + \sum_{t,j} \mu^i_j(t) \Big(x^i_j[\min](t) - x^i_j(t) \Big) \\
&\quad + \sum_{t,j} \nu^i_j(t) \Big(x^i_j(t) - x^i_j[\max](t) \Big).
\end{aligned} \tag{6}
$$

The first order conditions for a Nash equilibrium are given by:

$$
0 = \frac{\partial \mathcal{L}^i}{\partial x^i_j(t)} = \frac{\partial \psi^i(\underline{\mathbf{x}})}{\partial x^i_j(t)} - \eta^i_j - \mu^i_j(t) + \nu^i_j(t), \tag{7}
$$

which can be written as:

$$
\left(\gamma(D(t)) + \gamma'(D(t)) \left(\sum_k x^i_k(t) \right) \right) - \eta^i_j - \mu^i_j(t) + \nu^i_j(t) = 0, \tag{8}
$$

with the following complementarity conditions:

$$
\eta^i_j \geq 0 \qquad \text{and} \qquad \eta^i_j \Big(\sum_t x^i_j(t) - \beta^i_j \Big) = 0, \tag{9}
$$

$$
\mu^i_j(t) \geq 0 \qquad \text{and} \qquad \mu^i_j(t) \Big(x^i_j(t) - x^i_j[\min](t) \Big) = 0, \tag{10}
$$

$$
\nu^i_j(t) \geq 0 \qquad \text{and} \qquad \nu^i_j(t) \Big(x^i_j(t) - x^i_j[\max](t) \Big) = 0. \tag{11}
$$

Applying classical theorems (see *e.g.* [3]), we can find easily conditions which assure that an equilibrium exists and that it is unique if the $\gamma(D(t))$ function is strictly convex and increasing.

2.2 A competitive equilibrium model

The model of the previous subsection may be adapted to situation in which there are a consequent number of players. To do so, let us assume that each customer i is replicated n times with demand parameters β^i_j/n and bounds $x^i_j[\min](t)/n$ and $x^i_j[\max](t)/n$. This describes a game where the number of players increases while the influence of each player diminishes. The first order conditions for a Nash equilibrium (8) is now given by:

$$
\left(\gamma(D(t)) + \gamma'(D(t)) \frac{\sum_k x^i_k(t)}{n} \right) - \eta^i_j + \mu^i_j(t) - \nu^i_j(t) = 0. \tag{12}
$$

When $n \to \infty$ the conditions of a competitive equilibrium are met. Note that for each type of player i and type of service j, the following constraint must hold:

$$
\sum_t \frac{x^i_j(t)}{n} - \frac{\beta^i_j}{n} \geq 0, \tag{13}
$$

which is the same as (1). The same reasoning applies for the other constraints and, as a consequence, the KKT multipliers are the same as before.

In the large n limit, the term $\gamma'(D(t))\frac{\sum_k x_k^i(t)}{n}$ tends to 0, the condition (12) thus becomes:

$$\gamma(D(t)) - \eta_j^i - \mu_j^i(t) + \nu_j^i(t) = 0. \tag{14}$$

Each consumer is now a price taker. His decisions have no influence on the price. The quantities $x_j^i(t)$ are then determined by using (14) together with the complementarity conditions (9)-(11).

In [2] these games are shown to be similar to a class of games defined on transport or communication networks. In [4] the convergence of Nash equilibria to a traffic equilibrium called Wardrop equilibrium was proven along very similar lines to those exposed in this section.

2.2.1 A formulation as a linear program

In order to represent the supply side, let us consider a problem with m facilities (indexed by κ), n demands or TOU blocks (indexed by θ). The model is characterised by the following parameters[1]:

- ◇ Number of hours in demand block θ : H_θ,
- ◇ Cost per produced MWh by facility κ : c_κ,
- ◇ Capacity in MW of facility κ : K_κ.

Let $z_{\kappa\theta}$ be the energy flowing from facility κ during the time slot θ. If the timing of demands of type j for consumer type i were under direct control of the retailer, it would solve the following linear programme:

$$\underset{\{z_{\kappa\theta},\, x_j^i(\theta)\}}{\text{minimise}} \sum_{\theta=1}^{n}\sum_{\kappa=1}^{m} c_\kappa z_{\kappa\theta} \tag{15}$$

under the following constraints:

$$\begin{aligned}
\sum_{\kappa=1}^{m} z_{\kappa\theta} - \sum_{i,j} x_j^i(\theta) &\geq 0, && (16)\\
-z_{\kappa\theta} &\geq -K_\kappa H_\theta, && (17)\\
z_{\kappa\theta} &\geq 0, && (18)\\
\sum_{\theta} x_j^i(\theta) &\geq \beta_j^i, && (19)\\
x_j^i(\theta) &\geq x_j^i[\min](\theta), && (20)\\
x_j^i(\theta) &\leq x_j^i[\max](\theta). && (21)
\end{aligned}$$

These constraints correspond to the demand having to be met (16), the capacity having to be kept below its threshold (17) and the energy flows having to be positive (18). The dual variables for equations (16), (19), (20) and (21) are respectively given by π_θ, η_j^i, $\mu_j^i(\theta)$ and $\nu_j^i(\theta)$.

[1] In this model, no monthly variations nor discount factor are considered, but these are straightforward to implement.

By applying the optimality conditions for a linear programme and if the variables $x_j^i(\theta)$ are in the optimal basis, meaning that their reduced costs must be zero, we get the following:

$$\nu_j^i(\theta) - \mu_j^i(\theta) - \eta_j^i + \pi_\theta = 0. \tag{22}$$

This equation is to be compared with (14). The dual variable π_θ corresponds to the marginal production cost to satisfy demand. Therefore we conclude that (22) and (14) are identical. The other duality conditions would lead to similar complementarity conditions. Henceforth, *the solution of the linear programme gives the optimal response of consumers to a marginal cost pricing.*

Indeed the same result remains valid if one models the retailer over a long period with investment activities, as is done in the ETEM-SG model, for example (see *e.g.* [5]). In this case the price of electricity will be given by the long term marginal cost, which includes the investment cost.

3 ETEM-SG, an LTEP model with demand response and grid storage

ETEM-SG is an extension of ETEM (Energy/Technology/Environment Model), a model which is developed and maintained by ORDECSYS[2] and which belongs to the MARKAL/TIMES family of models. ETEM is implementing a linear programming approach. It has distinctive features in its implementation of stochastic programming and robust optimization techniques to deal with uncertainties. ETEM-SG takes into account the intermittency of electricity produced by renewables. Any variation of the weather conditions modifies the supply of electricity and hence its implicit price. The model represents a share of the demand for energy as flexible, *i.e.* a part of the forecast consumption can be shifted across time. This load shifting is triggered by the variation of these implicit prices. Pricing the electricity at its marginal cost of production sends the correct signal to DR-ready actors, as it has been shown in section 3.

A complete description of ETEM may be found in [6]. The global model structure is summarized in by Figure 1

The three main inputs in the model are (i) a description of the current energy system, (ii) an estimate of the evolution of the demands for services (such as heating, lighting, transport, etc.) and of their dynamics and (iii) the catalogue of technologies that can satisfy these demands. Under the assumption that the demands for services are inelastic, the model is then run as an optimization problem whose objective is to find the energy system with the minimum total discounted cost (including investments costs, operation and maintenance costs) over the horizon. The optimization is subject to several constraints of various nature: (i) technical constraints relating outputs to inputs for all technologies, (ii) technical constraints regarding the availability of technologies and limits on their flexibility, (iii) constraints of satisfaction of useful demands, bounds on imports and exports, emissions limits, etc.

3.1 Extending ETEM to Demand-Response

The time structure of ETEM is particularly important since the present study focuses on demands' dynamics and on the way one can exploit their flexibility. The typical time horizon of long-term energy planning models such as the ETEM model is of several decades. The *horizon* is divided

[2] `http://www.ordecsys.com/en/etem`

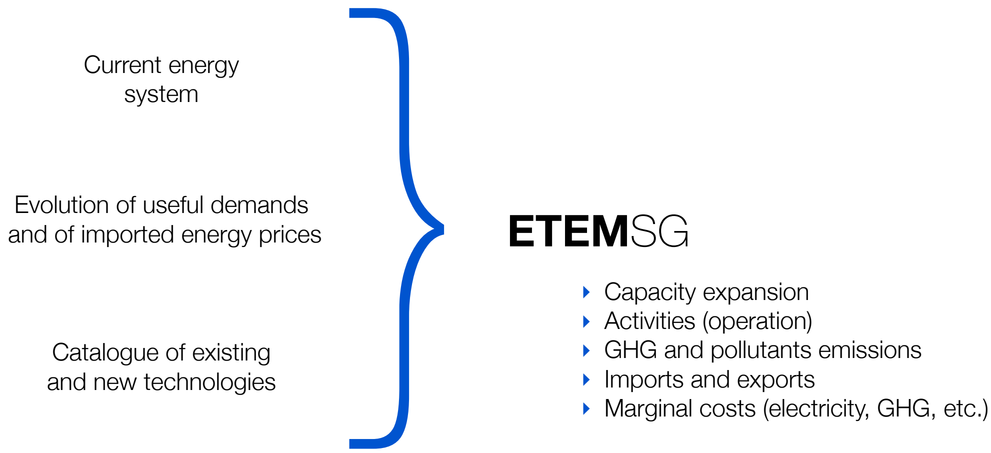


Figure 1: Workflow of the ETEM Model

in *periods*, typically 5-year long periods. The length of all periods need not be the same. Every period is further subdivided into *time-slices*, which divide the year into seasons and the days into representative sets of hours. In the case at hand, the following time structure has been adopted:

1. Horizon: 45 years (2005-2050),
2. Periods: 9 periods of 5 years, indexed by t,
3. Time-slices: 12 time-slices: S = (Winter, Summer, Intermediate) $\times$ (P1, M, P2, N) = WP1, WM, WP2, WN, SP1, SM, SP2, SN, IP1, IM, IP2, IN, where Winter = {January, February, March, October, November, December}, Summer = {June, July, August}, Intermediate = {April, May, September}, P1 = [6h, ..., 13h[, M = [13h-18h[, P2 = [18h-23h[, N = [23h-6h[, indexed by s. Time-slices are illustrated by Fig. 2.

The decision variables of the optimisation problem can be split in two categories: those depending solely on the periods t and those depending on both the periods t and the time-slices s. Investments are decided upon at each period t, so that the *capacity* is constant over the whole period. The capacity during a period t is given by the sum of the base-year (2005) capacity and the investments made during periods up to t[3]. The terms of the sum are weighted by a factor describing how the capacity decreases over time due to the finiteness of its lifetime. On the other hand, the way the capacities are operated (activities) depends both on the periods and time-slices. For example, a combined-cycle gas turbine could have a capacity of 100 MW and an activity of 38.64 GWh during SP1, if we assume an average efficiency of 60%.

$$\text{Period} \sim t \sim \text{Investments/Capacity} \qquad \text{Time-slice} \sim s \sim \text{Operations/Activity}$$

The time-slices encode the dynamics of the energy system during a day. The demands for services such as heating and transport are therefore specified for every period t and then allocated

[3]For an investment made at period $t^\star$ to contribute to the capacity of period t, the lifetime of the technology has to be greater or equal to $t - t^\star$.

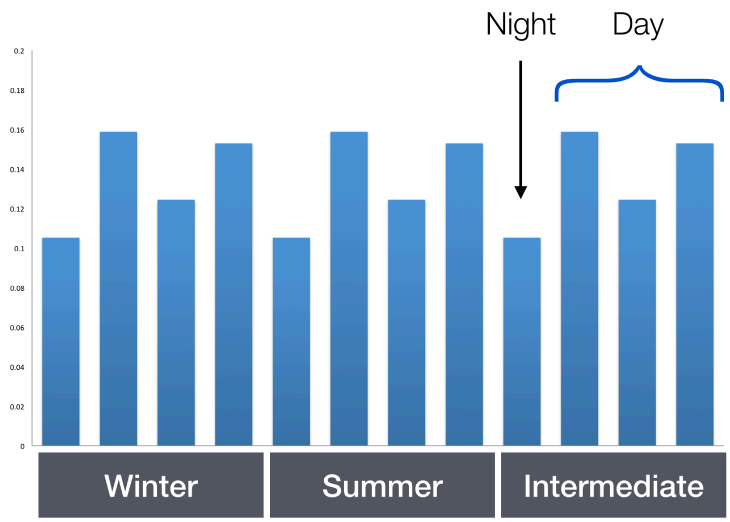


Figure 2: ETEM - Time-slices

to the time-slices s through a parameter called `frac_dem`: `frac_dem`(D, t, s) is the share of demand D allocated to time-slice s during period t. The `frac_dem` parameter thus obeys:

$$\sum_{s \in S} \texttt{frac\_dem}(D, t, s) = 1 \tag{23}$$

In other words, the `frac_dem` parameter serves as a representation of the shape of the load curve[4].

In order to allow the energy system to adapt to pricing signals, the `frac_dem` parameter has to be promoted to a variable, `VAR_frac_dem`. Due to the way the `frac_dem` parameter enters the equations of ETEM, we can promote it to a variable while staying in the realm of linear programming. Of course, further constraints have to be enforced.

Additional constraint 1

$$\sum_{s \in S_i} \texttt{VAR\_frac\_dem}(D, t, s) = \sum_{s \in S_i} \texttt{frac\_dem}(D, t, s) \tag{24}$$

where the S_i's are the seasons: S_1 is winter, S_2 summer and S_3 intermediate. These constraints ensure the entirety of the demand is met and forbid cross-seasonal load shifting.

Additional constraint 2

$$\begin{aligned} \Big(1 - \texttt{frac\_dem\_dev}(D, t, s)\Big)\texttt{frac\_dem}(D, t, s) &\leq \texttt{VAR\_frac\_dem}(D, t, s) \\ &\leq \Big(1 + \texttt{frac\_dem\_dev}(D, t, s)\Big)\texttt{frac\_dem}(D, t, s) \end{aligned} \tag{25}$$

where the `frac_dem_dev`(D, t, s) parameter quantifies the allowed deviation from the nominal value denoted by `frac_dem`(D, t, s). This parameter can depend on t since the share of the demand that

[4]Additional safety factors ensuring peak demand is met can be introduced.

can be shifted may evolve due to the progressive penetration of smart technologies. In order to estimate the parameter $\texttt{frac\_dem\_dev}(D, t, s)$, we proceed as follows. We first extract the value of $\texttt{frac\_dem}(D, t, s) = \texttt{frac\_dem}(D, t_0, s)$ from load curves. One then identifies the share of the demand that may be shifted across time and calibrate $\texttt{frac\_dem\_dev}(D, T, s)$. Finally, we assume a learning curve dictates the evolution of $\texttt{frac\_dem\_dev}(D, t, s)$. Several methods can be used to estimate the share of the demand that can be shifted. For example, a survey has been designed and rolled out in the French-speaking part of Switzerland to find out what could be the acceptance of demand response for residential electricity. The survey considered also the acceptance of using an electric car as a mean for grid storage. For other flexible demands (heating, warm water heating, some industrial processes), one can exploit estimates from the literature, see *e.g.* [7].

3.2 Dual use of Electric Vehicles

ETEM-SG can be used to evaluate the benefits of exploiting electric vehicles (EVs or PHEVs) as decentralized storage units. In a manner similar to DR, the underlying mechanism is based on time-varying tariffs. EVs could thus strategically recharge their batteries during time-slices of high energy production (i.e. low prices) and inject it back to the grid during time-slices of high demand (i.e. high prices). In such schemes, known as V2G (vehicle to grid), batteries would not only store energy to deliver a transport service but also to provide balancing services.

In ETEM-SG, the V2G option is implemented by allowing EVs' batteries to produce both regular electricity to be used for transport and electricity aiming at being injected back in the network. Figure 3 sketches the modelling of V2G. The electricity for storage (`ELS`) coming out the battery `BAT` during time-slice s is only allowed to enter `BAE` during later time-slices[5].

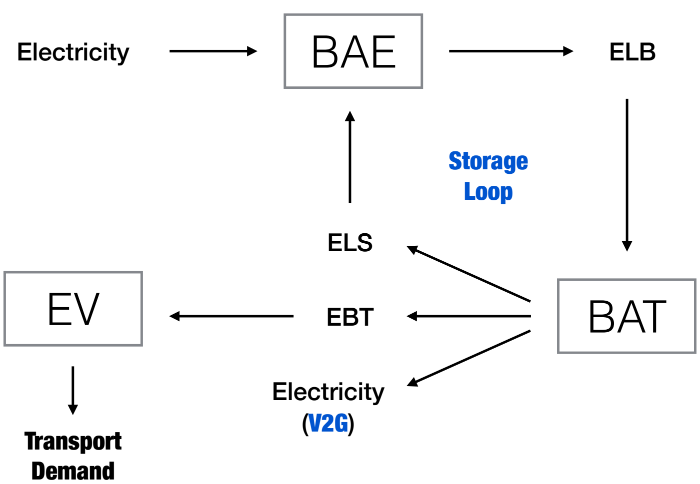


Figure 3: Schematic modelling of the V2G option in ETEM

Note that the number of batteries (*i.e.* technologies `BAE` and `BAT`) is constrained to be proportional to the number of EVs. The factor of proportionality is based on an average capacity of

[5]More in general, the `ELS` coming out the battery `BAT` during time-slice s is allowed to enter `BAE` in a set of time-slices called `Successors[ELS,`s`]`. Different energy storage technologies are characterised by different sets of `Successors`.

50 kWh per vehicle and is weighted by the acceptability of decentralised storage in EVs emerging from a survey we rolled out, see Section 3.4.1.

When studying the effect of V2G on the penetration of renewables we have assumed that direct injection of decentralised power production by renewables is limited. This constraint is implemented to mimic the power flow limitations imposed by electro-technical equipment such as transformers and distribution networks. One way to relieve the pressure imposed by decentralized production is to deploy distributed storage.

3.3 Defining Stochastic Weather Scenarios

The amount of investment in a given technology depends on several factors, among which one finds the availability factor of the technology. In this study, the *availability factor* of a given technology during time-slice s is defined as the proportion of s during which the technology can generate at peak power. For example, the average availability of nuclear power plants in Switzerland during the last 10 years did vary between 78.3% and 93.7% [8]. In order to correctly model the option value of solar and wind technologies, a stochastic treatment of their availability is necessary. The stochasticity is introduced in ETEM by letting the operations variable depend on random weather scenario, while keeping the investment variables independent of the weather scenario. Assuming m scenarios are equally likely, the optimization problem take the following schematic form:

```
minimise investment_costs + 1/m sum(weather in Scenarios) operations_costs(weather)

subject to:
     activity(weather) <= capacity, for all weather in Scenarios
     ...
```

The stochastic treatment of weather uncertainty (i) allows decision-makers to make robust decisions based on the performance of investments under contrasted weather scenarios, (ii) exhibits how the flexibility of the energy system (demand-response and storage) is used to adapt to weather conditions[6].

3.4 DR & V2G Calibration

In ETEM-SG one has to calibrate new parameters related to DR or V2G. First, one needs to tell ETEM how flexible the demand is through the new `frac_dem_dev`(D, t, s) parameter. Then storage has to be calibrated too, in particular by fixing the capacity of `BAT` per unit of electric vehicles capacity. Both these calibrations finally have to be weighted by a social acceptance factor to describe the willingness of the public to participate to such schemes.

3.4.1 Social Acceptance

Exploiting the energy system's flexibility crucially depends on the social acceptability of demand-response mechanisms and of decentralized storage in electric vehicles. To understand the drivers of the attractiveness of DR and storage in EVs, a survey has been made on a sample of 1041 people representative of population living in the French-speaking part of Switzerland. A similar survey is

[6]The variable `VAR_frac_dem`(D, t, s) is of course allowed to depend on the weather scenario: `VAR_frac_dem`$(D, t, s;$ weather$)$

planned for the Doha region. The aim of the survey is to understand which behaviur towards DR and storage in EVs people would adopt given that they (a) own DR-ready devices, (b) own an EV and (c) live in 2030. The main findings for the the French-speaking part of Switzerland are:

1. The attractiveness of DR schemes is relatively independent of its precise implementation characteristics, *i.e.* it exhibits a very low sensitivity to the studied parameters (the type of appliance, the control method, the importance of the time shift, and the financial incentive).

2. If provided with DR-ready devices, around **80%** of the sample would participate in DR schemes, even if the incentives are very modest.

3. The attractiveness of storage in EVs schemes is also relatively independent of its precise implementation characteristics, *i.e.* it exhibits a very low sensitivity to the studied parameters (battery ownership, guaranteed range, duration of service, financial incentive).

4. If provided with an EV, around **84%** of the sample would participate in decentralised storage schemes, even if the incentives are very modest.

3.4.2 DR Calibration

Once the social acceptance weight determined, it remains only to estimate the parameter called `frac_dem_dev`(D, t, s). Let us exemplify the procedure by considering residential electricity. First the `frac_dem`(D, t_0, s) is measured on a disaggregated load curve such as the one given in Fig. 4. To do so, we digitize the load curve with a 15 minute resolution and assign the load for each time-step to the correct time-slice s. Then, we normalize the result so that equation (23) is satisfied.

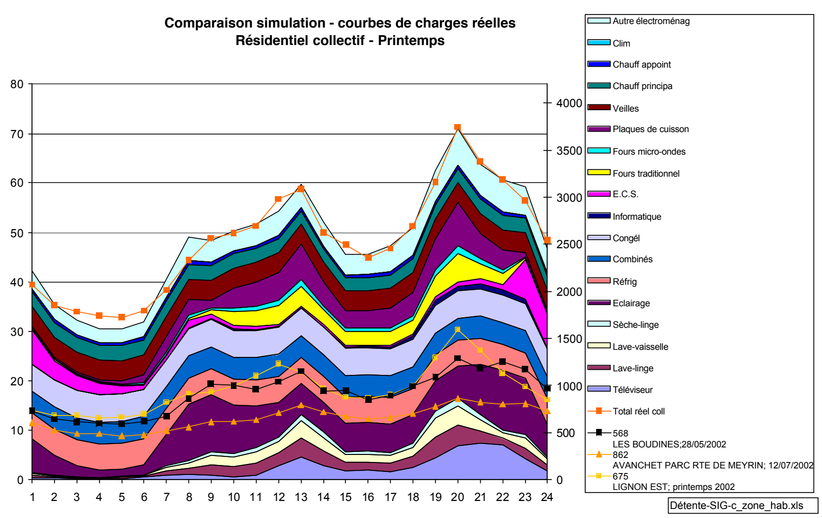


Figure 4: Prototypical disaggregated load curve used to calibrate DR

The next step is to identify which of the loads *could be* shifted. In our case, we considered dishwashers, washing machines, dryers, fridges and freezers to be flexible. From the digitised load curve, we know exactly the contribution of each of the considered appliances to the load curve $\texttt{frac\_dem}(D, t_0, s)$. To take care of load shifting within a time-slice, we divide the contribution of a given appliance by the number of times the maximum duration it can be shifted fits in the time-slice s.

From there, we know what is the fraction of the load curve $\texttt{frac\_dem}(D, t_0, s)$ that can be shifted across time. In order to compute the $\texttt{frac\_dem\_dev}(D, t, s)$ we multiply the previous result by the social acceptance factor. In the case at hand, as discussed in Section 3.4.1, this factor is 0.8 for the year 2030 and onwards. Between 2015 and 2030 we assume a learning curve taking the form of a sigmoid function dictates the evolution of the social acceptance factor. This completes the procedure for DR calibration[7].

3.4.3 V2G Calibration

To calibrate storage, we need to specify the storage process and characteristics of the storage device. The storage process is illustrated by Fig. 3. The only thing left to specify about the process is the set of time-slices allowed to receive energy stored at a given time-slice s. In the case of V2G, we have forbidden cross-seasonal storage. For example, the set of time-slices allowed to receive energy stored during summer nights (SN) are SM, SP1 and SP2. Once the process is accurately described, it only remains to relate the capacity of the battery with the number of electric cars. The capacity of transport is expressed in thousands of vehicle-kilometre per day, while the capacity of a technology is measured in GW. In Switzerland, a vehicle on average covers a distance of 32.8 kilometres per day [9]. One unit of capacity is therefore equivalent to a fleet of around 30.5 vehicles. If one assumes each EV is provided with a 50 kWh battery on average, the storage capacity of one unit of EVs is 1525 kWh. To translate this into a maximum power that can be injected into batteries, it is sufficient to divide by the number of hours per day in each time slice. Let us for example consider SM, whose daily duration is 5 hours. In order not to overshoot the capacity of the battery (1525 kWh), the maximal power should be less than 305 kW per unit of EV capacity. A ratio of $3 \cdot 10^{-4}$ thus relates the capacity of the batteries to the one of electric vehicles. Finally a social acceptance factor taking the form of a sigmoid function reaching a maximum of 0.84 (see Section 3.4.1) multiplies this figure.

4 Application to the Arc Lémanique region

4.1 The Arc Lémanique data

In order to identify the potential role demand-response and storage in electric vehicles could play in the energy transition, we illustrate it on the Arc Lémanique region (Cantons of Vaud and of Geneva), which was home to 1.22M inhabitants in 2013. The model considered in the following is based on the ETEM model that has been developed during the RITES project [6], which was supported by the Swiss Federal Office of Energy. The total energy consumption of the Arc Lémanique in 2010 was 114.3 PJ (VD: 73.3 PJ [10], GE[8]: 41.0 PJ [11]). The overall 2010 CO_2 emissions amounted to 5.48 Mt (VD: 3.49 Mt [12], GE: 1.99 Mt [11]). Note that the region is a net importer of electricity, as

[7] Note that we have assumed the allowed deviation from $\texttt{frac\_dem}(D, t, s)$ to be symmetrical (see equation (25)). Asymmetries could be introduced in a straightforward way.

[8] This figure does not include neither CERN's electricity consumption nor the fuel consumption of Geneva International Airport.

exemplified by the 2010 data (VD: ~ 3.3 TWh [10], GE: 2.2 TWh [13]). The potential for renewables in the Arc Lémanique region used in this illustration is established in the RITES project [6] under quite conservative assumptions.

4.1.1 The Arc Lémanique Region and the Swiss Energy Strategy 2050

The *Neue Energiepolitik* (NEP) scenario of the Swiss Energy Strategy 2050 [16] is used in this Chapter to demonstrate the systemic effects of demand-response and decentralised storage and thereby to illustrate how models such as ETEM can be used to design and assess the effectiveness of energy/climate policies.

In particular, in the NEP scenario, the emissions of greenhouse gases are caped at a level of 1.5 tons of CO_2-eq per person in 2050. Since the population is expected to attain 1.37M people in the Arc Lémanique region by 2050 ('mittleres' Szenario A-00-2010), the total 2050 emissions should not exceed 2.1 Mt CO_2-eq.

In the NEP scenario, the 2050 energy demand is expected to be 46% lower than the 2010 demand [16]. However, since the ETEM model is phrased in terms of demand for services, *e.g.* a number of square metres to heat at a given temperature, the level of the demands will not follow the same downward trend as the energy demand of the NEP scenario, but rather increase proportionally to some indicators (*e.g.* GDP evolution, population growth). Note that the parameter driving the energy demand for heating in the housing sector also takes into account effects such as the increasing number of square metres per person and the decreasing number of people per house/apartment. In order to satisfy the final energy demand constraint of the NEP scenario, virtual technologies that for example mimic thermal insulation or refurbishment of buildings are introduced.

The energy reduction effort is spread amongst sectors as indicated in Table 1, see Table 5-10 of [16]:

Sector	**Δ (2050 vs 2010)**
Heating	64.2%
Warm water	15.5%
Industrial heat	43.4%
Lighting	57.1%
HVAC	-71.0%
ICT	18.4%
Industry	20.0%
Transport	53.7%
Others	-28.8%
Overall	**46.4%**

Table 1: Energy consumption effort allocated to sectors

4.1.2 Exogenous Parameters

Import prices and techno-economic parameters for each of the technologies in the ETEM catalogue are exogenous parameters. Import prices and their foreseen evolution are mostly based on IEA data [17, 18]. ORDECSYS has created and maintains a database of techno-economic parameters for each of the technologies entering the modelling effort. These parameters include the investment cost per unit of capacity, the operations costs per unit of activity, the maintenance costs per unit of capacity, the lifetime, the efficiency, the availability and the greenhouse gases emissions per unit of activity. See [6] for an overview of the database used in this project. Note that a similar effort undertaken by the IEA-ETSAP group has resulted in a publicly available database [19].

4.2 Numerical results

In this section, we illustrate the model used by exhibiting some of the results related to demand-response and to storage in electric vehicles (V2G). These mechanisms have system-wide impacts, among which (i) penetration of EVs, (ii) penetration of renewables, (iii) modification of the electric load curve, (iv) modification of the CO_2 abatement effort distribution.

4.2.1 Scenario Definition

The scenarios that will be considered in this section are given in Table 2.

Scenario 1	NEP	Reference scenario
Scenario 2	NEP $-$ CO_2	Reference without CO_2 constraint
Scenario 3	NEP + DR	Reference with Demand-Response
Scenario 4	NEP + V2G	Reference with V2G
Scenario 5	NEP + DR + V2G	Reference with Demand-Response and V2G

Table 2: Definition of scenarios

where the Reference case is the one described in the NEP scenario. Thanks to the structure of the ETEM model, adding and removing constraints is effortless. In the case at hand, the problem consists of around 200k variables and 240k constraints, and is solved by MOSEK in around a minute on a 4 CPU machine.

4.2.2 Penetration of EVs

As a first example, let us consider the penetration of electric vehicles. It can clearly be seen on Fig. 5 that, from a systems point of view, it is the CO_2 emissions' cap that encourages the adoption of EVs. In the unconstrained scenario (NEP $-$ CO_2), the emissions remain at the current level. In the NEP scenario, EVs first appear in 2030. Their appearance is delayed in the case DR mechanisms are at work. Indeed, when DR is available it can be used to help achieving the supply-demand balance. Only when this potential is exhausted the electric vehicles become attractive due to their dual use as decentralised storage units.

When one allows EVs not only to store energy to provide transport services but also to inject power back to the grid (V2G), EVs can facilitate the penetration of renewables even more. One can see by comparing the scenarios NEP + V2G and NEP + DR + V2G on Fig. 5 that the model indeed exploits this potential. Here again, allowing DR mechanisms delays the appearance of EVs on the market.

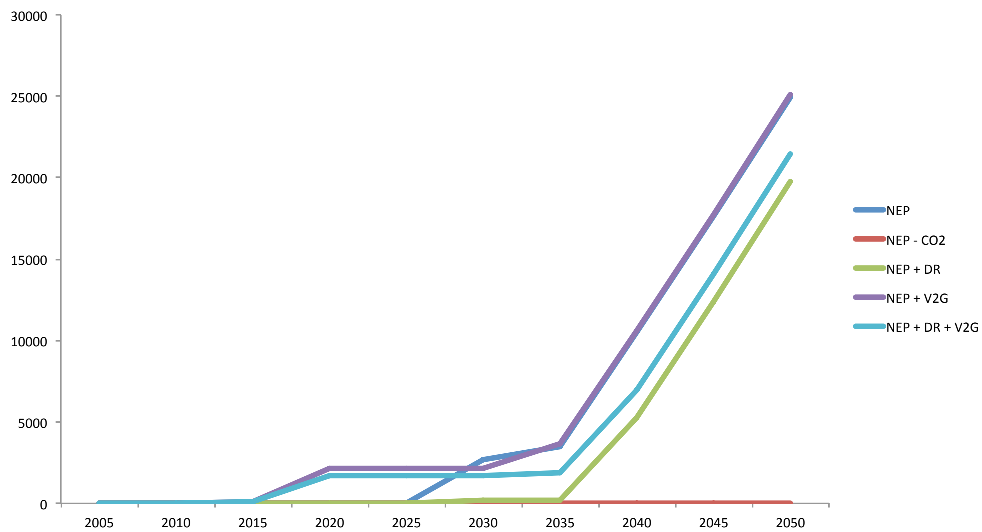
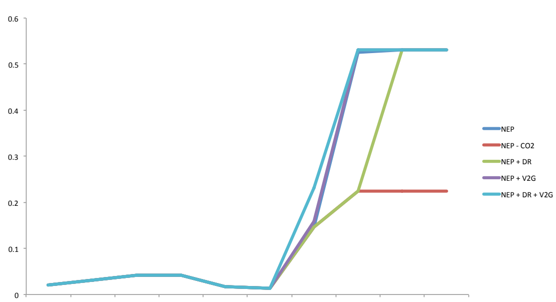


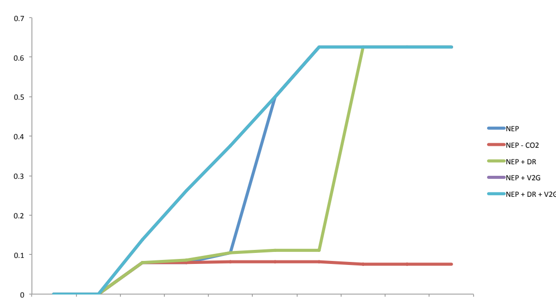
Figure 5: Penetration of EVs

4.2.3 Penetration of Renewables

As anticipated above, the penetration rates of EVs and of renewables are tightly bound together. Indeed, since we have assumed limits on decentralised direct injection, which are motivated by technical constraints, investments in decentralised storage have to be made in order to foster the integration of renewables. In the case at hand, it is EVs that provide this service. The penetration of PV and wind turbines are shown on Fig. 6. In the NEP scenario, wind turbines reach their maximum capacity in 2035, time at which PV begin to penetrate more substantially. This phenomenon may be understood as emerging from the "financial competition" PV and wind turbines fight to use EVs' batteries. The benefits of using EVs' batteries are larger for wind technologies than for PV since the overlap between the wind production pattern and the demand is much worse than the one between solar irradiation and the demand.



(a) Photovoltaics



(b) Wind turbines

Figure 6: Penetration of intermittent renewables

Demand-response again change the picture considerably. Since such mechanisms result in a more intensive use of existing assets (through a flattening of the load charge due to a quest for a minimisation of the marginal price of electricity), renewables are not competitive enough to substantially raise their penetration before 2040. At this point, the CO_2 emissions cap becomes tight enough to force the penetration of renewables.

On the other hand, V2G technologies have an interesting impact on the penetration of wind turbines. Since with V2G, EVs' batteries can be used not only to store energy to provide transport services at later times but also to inject power back to the grid, both EVs and wind turbines substantially penetrate as can be seen from Figures 5 and 6(b). In this case too, wind turbines are more attractive than photovoltaics since the latter have a greater overlap with the demand. Wind turbines thus make EVs profitable through their dual use as decentralised batteries.

4.2.4 Electricity Imports

Electricity imports are important in the Arc Lémanique region. As stated in Section **??**, both the Canton of Vaud and the Canton of Geneva are net importers of electricity. In most scenarios the electricity imports are first decreasing as a consequence of the reduction of energy use in the NEP scenario. At later times, the CO_2 constraint is becoming harder to satisfy and thus imports[9] raise, in particular to satisfy the electricity demand from EVs.

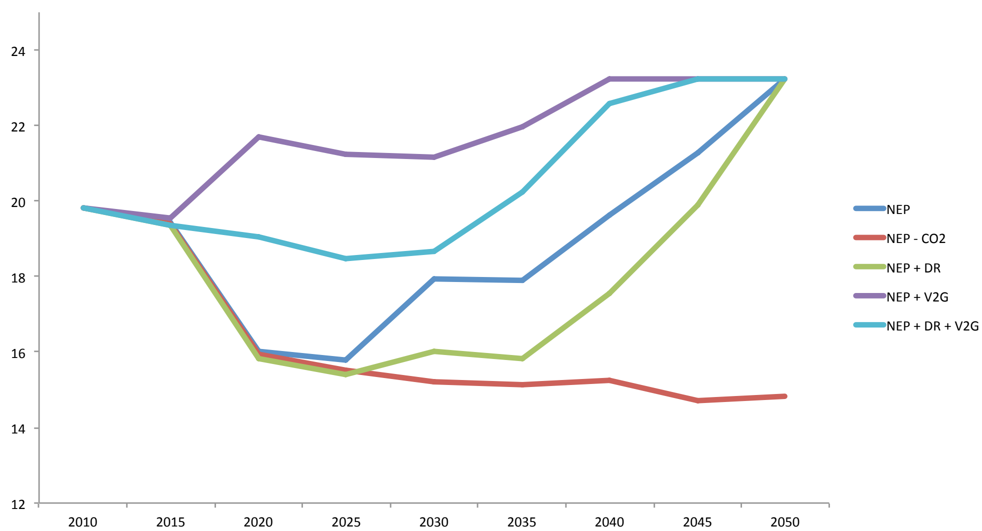


Figure 7: Electricity imports in PJ

Since exploiting the flexibility of the demand *via* demand-response strategies can be translated into a more intensive use of generation plants (less peaking plants are required), DR results in a decrease of electricity imports. V2G, on the other hand, tends to increase the imports. Indeed, in such schemes, EVs are interested in buying electricity during low prices periods and then in selling it during high prices ones (arbitrage). When both DR and V2G are active, imports remain approximately constant until 2030 and then raise to help satisfying the CO_2 constraint.

[9]Imports are considered as being carbon-free in this modelling exercise. Mimicking a carbon tax on imported electricity would be of no difficulty.

4.2.5 CO_2 Abatement Effort

As previously mentioned, the NEP scenario of the SES2050 aims at reducing GHG emissions to at least 1.5 tons of CO_2-eq per capita by 2050. Without any constraint, the techno-economic optimum would to continue emitting GHG at today's level on the whole horizon.

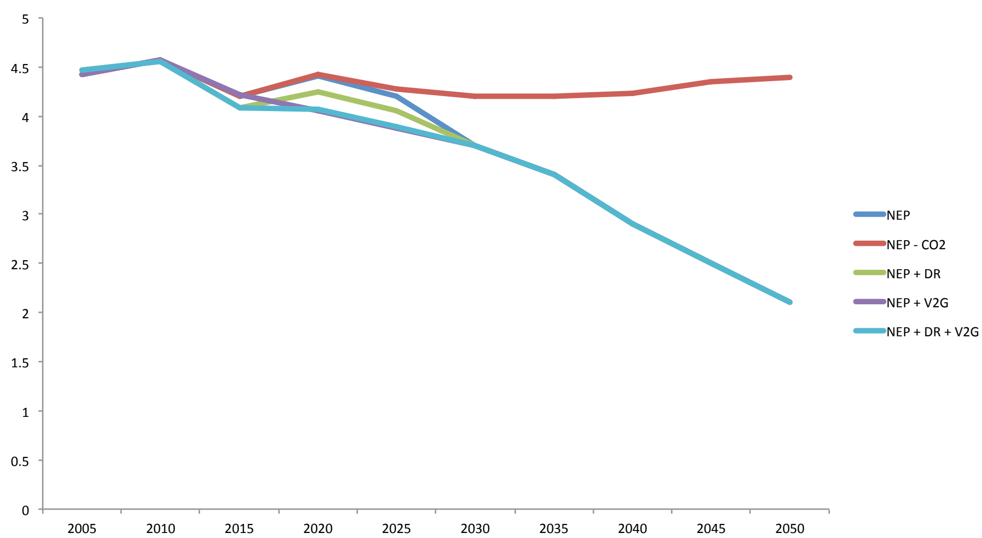


Figure 8: CO_2-eq emissions

The trajectories to attain the objective of 2.1 Mt of CO_2-eq by 2050 do not differ much. We can however notice that both DR and V2G are acting as facilitators between 2015 and 2030. More interesting effects can be seen from the distribution of the effort amongst the different sectors, as exhibited by Fig. 9.

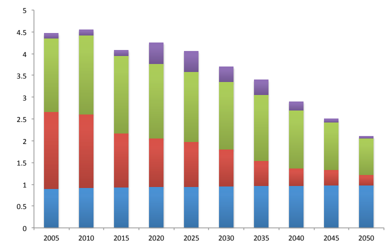
By comparing Figures 9(a) and 9(c), one can clearly witness the influence of introducing DR mechanisms in the residential sector. Residential emissions almost decrease by a factor of 2 thanks to DR. One can further note that decentralised storage results in less emissions in the energy sector. This is mainly due to the more efficient integration of renewables made possible by the exploitation of V2G strategies.

4.2.6 Effect of DR on the Load Curve

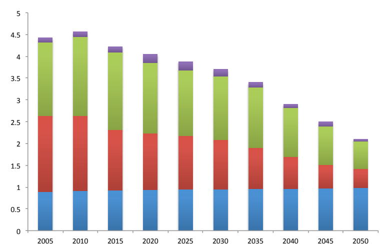
One of the main targets of DR mechanisms is to exploit the inherent flexibility of the demand in such a way as to facilitate the balancing of supply and demand. The way flexibility is used should therefore depend on local conditions (availability of renewables, electricity pricing scheme, demand elasticity, etc.) and thus change every day. However, due to the time structure of long-term planning models such as ETEM in which each time-slice s is a representative of several occurrences (WN is representing all winter nights), the dynamic adaptation of flexible loads to local conditions cannot be precisely grasped. ETEM can nevertheless seize opportunities emerging from demand flexibility to adapt its load curve, which thus has the same profile for all winter nights. In order to overcome these limitations, a *chronological* optimisation-based simulation model would have to be used. Fig. 10 shows how the 2050 load curve changes when DR is allowed, using the representation introduced in Fig. 2.

(a) NEP

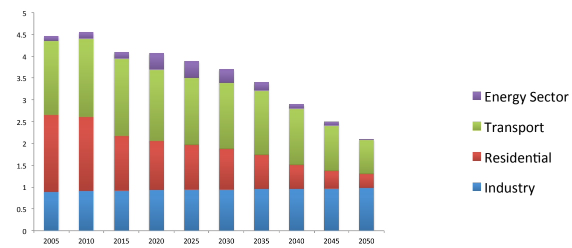
(b) NEP - CO_2



(c) NEP + DR

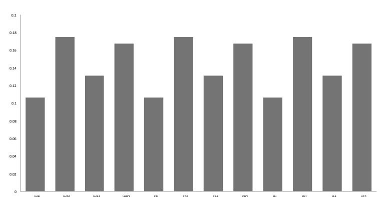


(d) NEP + V2G

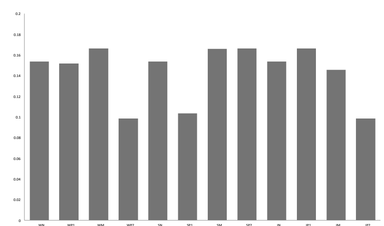


(e) NEP + DR + V2G

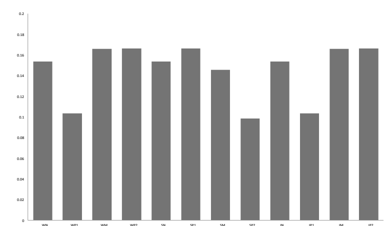
Figure 9: Distribution of CO_2 abatement effort amongst sectors



(a) NEP



(b) NEP + DR



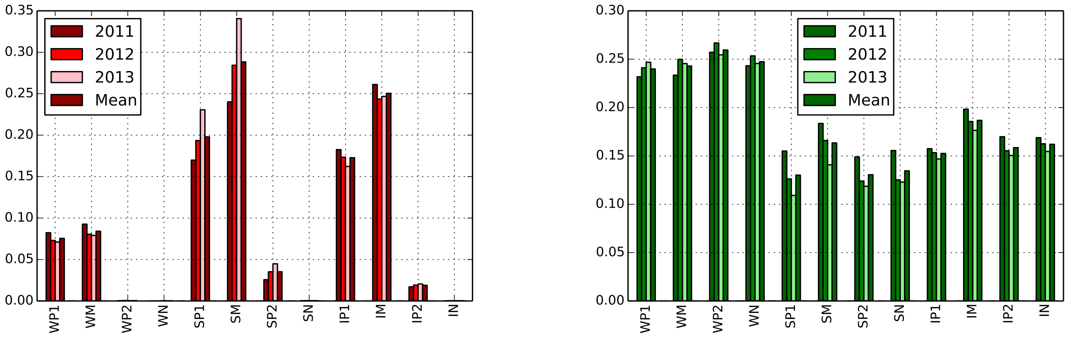
(c) NEP + DR + V2G

Figure 10: Load curve modification due to DR in 2050

Our analyses show that the modification of the residential electricity load curve (e.g. going from Fig. 10(a) to Fig. 10(b)) results in a flattening of the total electricity load curve, as one would expect.

4.3 Stochastic Analysis

The aim of the stochastic analysis is to demonstrate how investment decisions are taken when uncertainties are present. In the following we focus our investigation on the penetration of EVs, the penetration of renewables and the adaptation of the demand pattern to weather conditions *via* DR mechanisms. The stochastic analysis follows the principle introduced in Section 3.3, *i.e.* three weather scenarios (which uniquely determine the quantity of electricity produced per unit of capacity of photovoltaics and of wind turbines during each of the time-slices $s \in S$) are constructed from EEX PV and wind turbines production statistics for the years 2011 to 2013 [20]. The resulting availability factors are shown on Fig. 11. Investment decisions are independent of the weather scenarios whereas the way assets are operated is allowed to depend on the weather scenario.



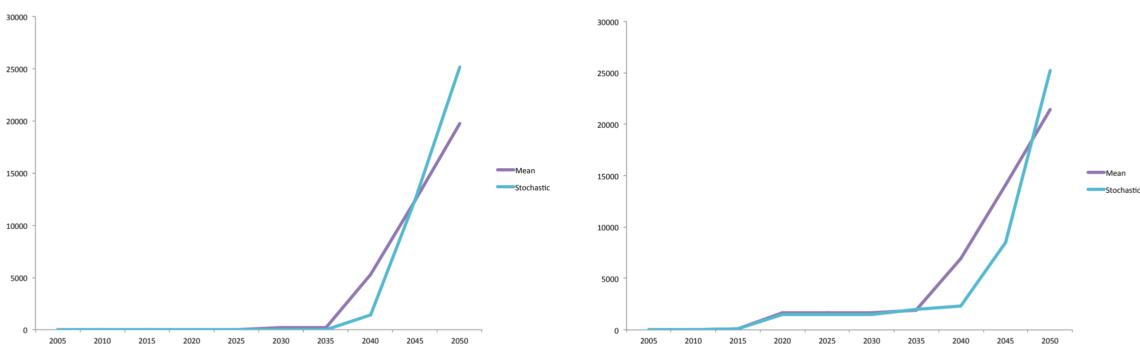
(a) Photovoltaics

(b) Wind turbines

Figure 11: Availability factors for the three weather scenarios

4.3.1 Penetration of EVs

In Fig. 12, we compare investment decisions when the model is run in a deterministic mode (mean of the 2011, 2012 and 2013 weather scenarios) with the investment decisions emerging from the stochastic analysis. The two illustrations respectively correspond to the NEP + DR and the NEP + DR + V2G scenarios. In this illustration, we can clearly notice that EVs penetrate at a lower rate due the uncertain environment. At the end of the horizon, the penetration of EVs is growing fast in order to meet the cap on CO_2 emissions.



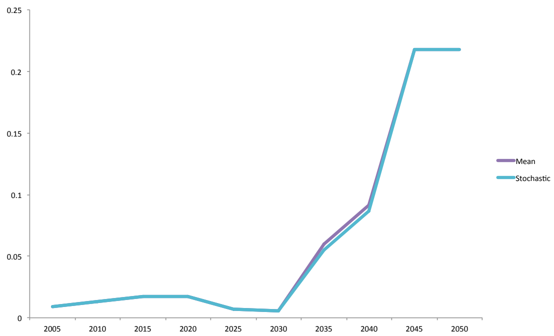
(a) NEP + DR

(b) NEP + DR + V2G

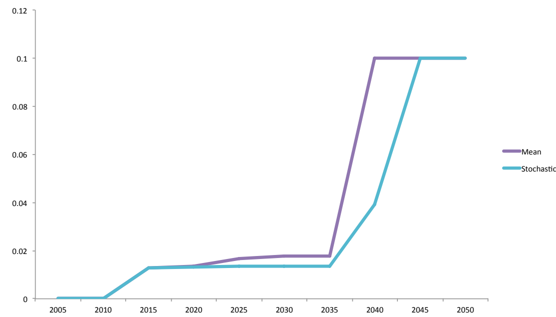
Figure 12: Uncertainties tend to delay the penetration of EVs

4.3.2 Penetration of Renewables

In the NEP + DR + V2G the penetration of renewables remains the same as in the deterministic setting even if the environment is uncertain. This fact is caused by the additional attractiveness gained by renewables when V2G is available. Even if the environment is uncertain, the systemic benefit are such that investment decisions remain unchanged. However in the NEP + DR scenario, the picture changes as indicated by Fig. 13. The uncertainties in the availability of wind turbines make them less attractive than in a deterministic setting. In contrast, the penetration of photovoltaics is almost unchanged since the overlap between the production and the demand is important, even if it is uncertain.



(a) Photovoltaics



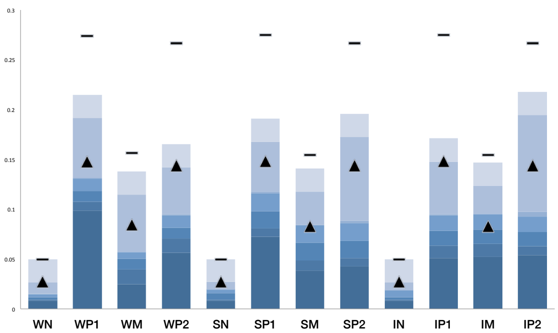
(b) Wind turbines

Figure 13: Uncertainties tend to delay the penetration of renewables in the NEP + DR scenario

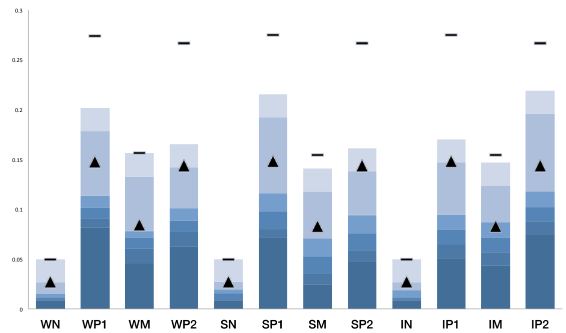
4.3.3 Dynamic Adjustment of the Demand

The aim of the stochastic modelling is to find a set of investment decisions that can cope with all the considered weather scenarios. By comparing the activities of the technologies for each of the three weather scenarios presented in Fig. 14, one can check whether the system fully exploits its flexibility.

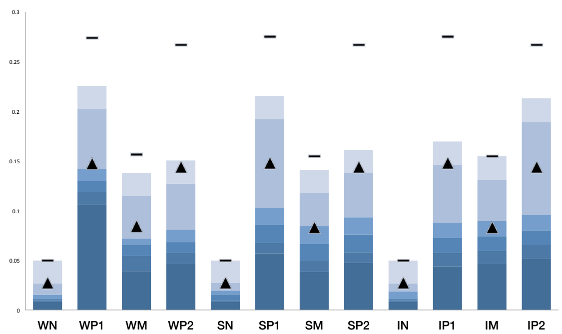
The different colour levels on Fig. 14 correspond to different technologies. One can first notice that thanks to well-engineered constraints the share of any given technology remains almost constant across time-slices. This is the behaviour one expects for distributed technologies such as those satisfying heating demand. The triangles and dashes respectively indicate the lower and upper bounds of the heating load curve. One can in particular notice that the flexibility available during night-time is always exploited at its maximum in all three weather scenarios.



(a) Scenario 2011



(b) Scenario 2012



(c) Scenario 2013

Figure 14: Adjustment of the heating load curve in the NEP + DR + V2G scenario

5 SESCOM: a Modeling approach for smart energy and technology choices in smart cities

Several methodological improvements could be brought to refine the analyses of the potential role of smart technologies in regional energy systems: (i) One may consider the fact that the electricity prices are not equal at each node of the electricity grid due to local congestion issues. The *locational marginal prices* would therefore constitute an even better price signal to mobilise the demand flexibility. (ii) An optimization-based simulation tool with *chronological* time-slices would allow to better study the dynamical adaptation of the demand to weather conditions. In particular this tool could validate the investments decisions of ETEM by simulating the yearly operations with an hourly time-step. (iii) A model interconnecting several regional ETEM-SG sub-models would allow for a better assessment of the role demand response and grid energy storage could play in a country energy transition.

These developments are part of the goal of SESCOM - Smart Energy for Smart City Operational Model - a model for the long term market allocation of sustainable and smart technology in urban sustainable development. The model is designed as a support tool for the analysis of energy transition strategies for countries or regions where smart cities are developing.

5.1 SESCOM overall structure

In Fig. 15 the structure of SESCOM is summarized. The model encompasses one or several urban regions and some elements of the energy transport and transmission system, in particular for natural gas and electricity. The model will represent the main constraints in energy transport and distribution, with an adequate spatial granularity.

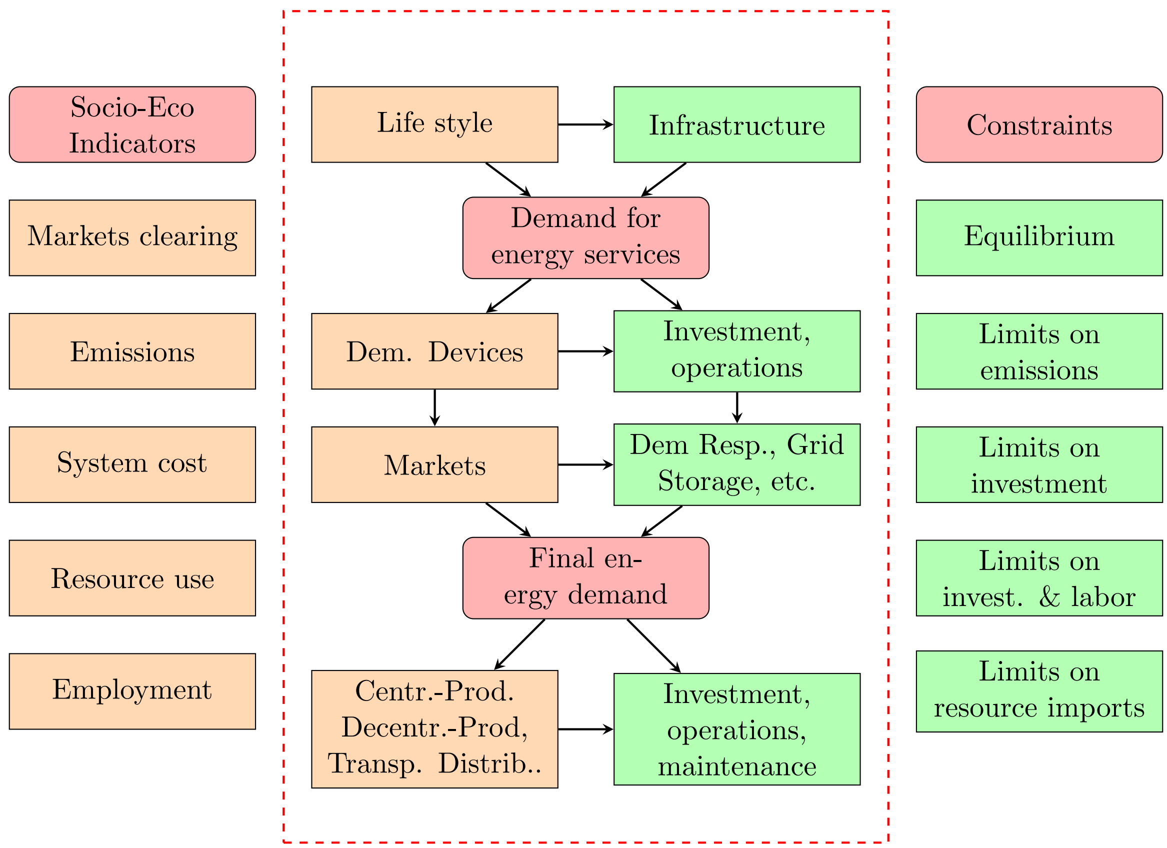


Figure 15: SESCOM structure

The model has two time scales: In the long term time scale (time horizon of 50 years with 1 to 5 year periods) it has the structure of a capacity expansion model. In the short term time scale (time horizon of one year, with fractions of day periods), it has the structure of a production-storage-distribution model on a power grid. A set of socio economic indicators are used as drivers of the growth of demand for different types of services.

The coordination of the many agents involved in the day-to-day functioning of the smart energy system is performed through market based mechanisms, with marginal cost pricing. The long term and short term models are linked in two ways: (i) the short term model will inherit the installed capacities in various technologies, as decided in the long term model; (ii) the long term model will obtain from the short term model a calibration of the demand response and grid storage capacities offered in the smart energy system.

5.2 Life styles and infrastructure investments influence useful demands and technology options

At the highest level in the model we represent the influence of new life styles on smart city development and the options to invest in new infrastructures. This could be e.g. the adoption of new designs for buildings, the development of new public transport networks, the dissemination of smart meters, etc. By anticipating life style changes and identifying possible initiatives concerning the development of new infrastructure one could relate an ensemble of discrete policy choices with scenarios of evolution of useful energy demands, *i.e.* demands for different categories of energy services. The list of services, for which some form of energy should be supplied through appropriate use of demand devices, includes in particular

The evolution of demand for these services will be driven by some indicators related to demography, economic growth, urbanism, changes in life-habits, speed of dissemination of the information and communication technologies. At this level, the model is a decision tree, as shown in Fig. 16

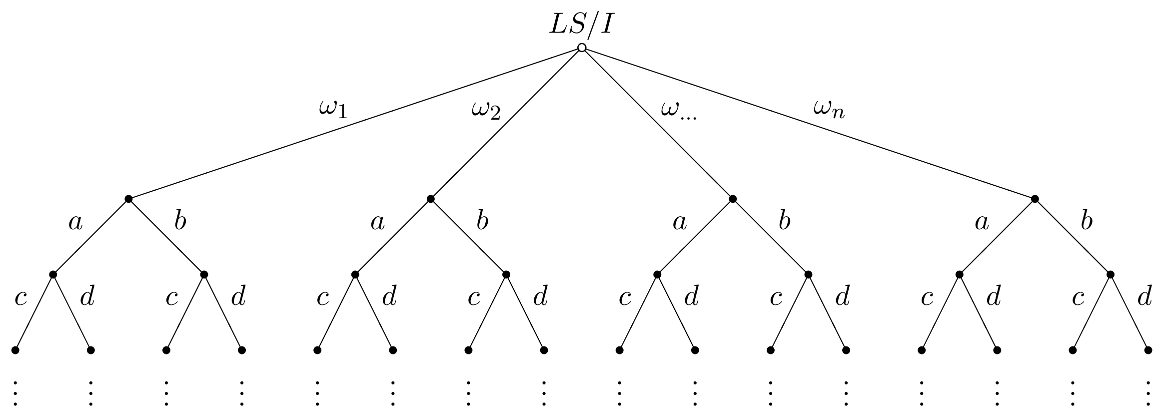


Figure 16: The Life Style / Infrastructure choice and scenario tree

where initial branches, labelled $\omega_1, \ldots, \omega_n$, correspond to initial choices of life styles and major infrastructure investments. Each branch leads then to an event-tree describing the possible (random) evolution of useful demands, the international price of energy forms, the environmental constraints, the availability and efficiency of new technologies, etc.

6 Conclusion

In this paper, we have presented an innovative methodological framework for assessing the potential benefits of developing demand-response (DR) mechanisms and of exploiting electric vehicles as decentralised storage units (V2G) in the context of energy transition policies. Both these mechanisms are taking advantage of the price sensitivity of the demand. It is indeed well recognized that part of the demand is flexible, in the sense that the precise moment at which it is satisfied is not important to the end-user. We have shown how demand response (DR) induced by adaptive pricing could be represented in a linear program. This insight has been used to an enhance the long-term energy planning model ETEM-SG to include DR and V2G mechanisms.

Improvements in ETEM

- The integration of demand-response in ETEM, which allows the demand-side to dynamically adapt to the status of the electricity sector through price signals (marginal cost pricing).
- The description of V2G mechanisms, *i.e.* the dual use of electric vehicles through which EVs' batteries not only produce regular electricity used to satisfy transport services but also electricity aiming at being injected back into the electricity grid.
- The stochastic treatment of weather conditions to help practitioners in their decision-making process.

Survey Thanks to a survey we have designed with the help of the project's stakeholders, we have been able to measure the social attractiveness of DR and V2G mechanisms. It turns out a clear majority of the sample would engage in such schemes even if the financial incentives are very modest. This can be interpreted as the willingness of the population to accept behavioral adaptations may be necessary to successfully achieve the transition towards a more sustainable energy sector. This can be linked with the French initiative EcoWatt in which the end-users are asked to diminish their consumption during critical periods without any financial benefits (but avoiding a blackout).

Main findings A case study on the Arc Lémanique region has been implemented in order to identify the potential role DR and V2G could play in the energy transition. Different scenarios have been considered, each one being a modulation of the "Neue Energiepolitik" scenario engineered by Swiss Federal Office of Energy in the Swiss Energy Strategy 2050 [16]. The main findings are:

1. Demand-response tends to decrease the attractiveness of electric vehicles since the latter have fewer opportunities to arbitrage between periods of high prices and periods of low prices.
2. Demand-response tends to decrease the attractiveness of intermittent renewables. Since exploiting DR translates into a flattening of the load curve and thereby into a more intensive use of assets, fewer investments in generating capacities are needed. Intermittent renewables are particularly exposed because of their intermittent production patterns, which cannot fully be absorbed by the flexibility considered within this study.
3. Decentralized storage in electric vehicles tends to increase the attractiveness of renewables, in particular of wind turbines. Indeed, coupling electric vehicles with wind turbines has a greater systemic benefit than coupling them with solar panels due to the respective overlaps of solar and wind production with the demand.
4. The stochastic analysis reveals that investments in renewables and electric cars tend to be more beneficial if delayed compared to the deterministic setting. However, this comes at the price of a dramatic increase of both renewables and electric vehicles in the 2040s to satisfy the emissions reduction objective.

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