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BOTTOM-UP MODEL FOR LOCAL GAS AND ELECTRICITY INTERACTIONS WITH HYBRID TECHNOLOGIES

C. Vuillecard

France

ABSTRACT

Interactions of gas and electricity distribution network through hybrid technologies might offer potential benefits for the whole energy infrastructure. Yet the impact of distributed hybrid technologies, micro-cogeneration and hybrid heat pumps, on gas and electricity loads is difficult to predict and is dependent on building stock and energy practices among other variables. This article proposes a methodology to build an Engineering Bottom-Up model which is consistent with regional top-down data. The structure of the model is presented, and finally a case study illustrates expected results from the model. The developed approach will help regional planning decision maker to consider hybrid gas-electricity technologies.

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1 INTRODUCTION

1.1 Context and background

European gas demand of residential and industrial sectors are expected to have a limited growth. In France, the main gas transport system operator even expects a decrease of 0.2% of the gas load at peak conditions [1]. This rate is the average annual rate foreseen for the next 10 year period. In fact, many reasons justify such an assumption: political commitment regarding energy consumption reduction, insulation of the national building stock ... On the other hand, the gas demand on transport network is supposed to increase due to power generation through combined cycle power plants. Many projects are blooming in the northern European countries to ensure the security of electricity supply and cope with the growth of electricity peak demand (significant increase in France [2] in recent years).

Another element of the context is the evolution of distribution networks. Tomorrow, energy infrastructures will be oriented toward smart solutions, especially in electricity where Smart Grid is gaining momentum. This evolution is mainly justified by the integration of renewable energy, and peak load management. Load shifting and/or shedding are potential leverages offered from smart solutions to optimise electricity infrastructure. In addition, new gas technologies such as micro-cogeneration and hybrid heat-pumps may offer a good opportunity to optimise electricity network and play a role in smart grid deployments. Indeed, such systems are onsite solutions that have the ability to interact with electricity demand. Furthermore, if the dispatch of electrical loads and storage management are key issues to deal with daily variations, no seasonal storage solution seems viable in the mid-term considering the technical and economical equation. Hence, distributed hybrid gas-electricity technologies might bring benefits to local electricity grid without significant impact on the gas network.

The overall benefits would be:

- To reduce electricity grid losses ;
- To relieve electricity network capacity, because electricity peak demand is highly correlated with heating demand in winter (especially in some countries like France).
- To stabilise gas distribution transit, and hence optimise the overall energy gas-electricity infrastructure
- To enhance global efficiency with onsite solution.

1.2 Motivations

The study deals with micro-cogeneration and hybrid heat pumps. Micro-cogeneration, or micro combined heat and power (µCHP), has the ability to produce electricity locally while electricity demand is high in winter; and hybrid heat-pump can switch from electricity to gas in order to limit electrical load. Indeed, correlation of low temperature and electricity demand is high and investigated in [3] for different cities. The purpose of this work consists in quantifying the impacts of gas technologies on gas and electricity infrastructures. This part is essential to answer the key question: is it viable to deploy new distributed gas technologies; against centralised solutions that benefit from significant economy of scale? Gas and electricity distribution network interactions may effectively provide significant benefits to energy infrastructures, but how much?

The degree of precision required, and thus the number of inputs, is related to spatial and temporal scales. If interested in individual household loads it seems difficult to draw conclusion from a modelling framework. Experimental field tests are more relevant to investigate real behaviours of loads. For instance Vuillecard et al presented impact results from field test measurements. Figure 1, extracted from [4], illustrates the potential of µCHP to relieve electricity demand in winter for a group of 40 dwellings in France equipped with Stirling engine gas boilers. This chart shows that this technology can generate nearly half of the electricity demand in gas heated dwellings in winter time. In term of load management, micro-cogeneration reduced the peak demand up to 34 % in January and 17% through the entire year [4].

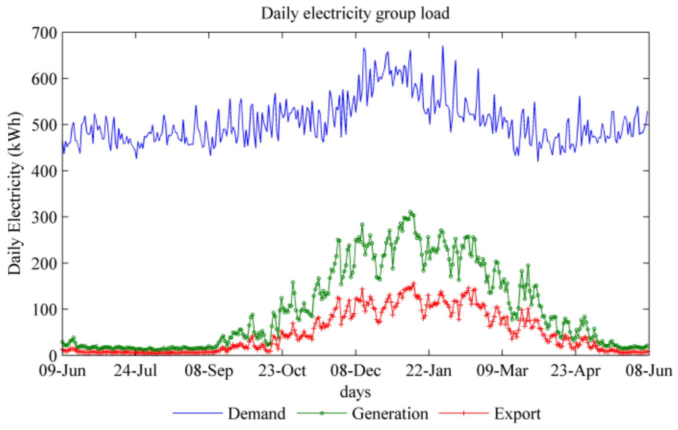

Figure 1 - electricity demand, and generation from µCHP

On the other hand, if interested in a zone of residential area of a city or a region, it seems impossible to set up a complete instrumentation of each dwellings but instead modelling appears to be the only way. And our motivation is guided by the will to quantify the impact of hybrid technologies to an aggregate load of a region. Aggregate loads are easier to handle due to the statistical aggregation. Indeed, to a certain extent, aggregate electricity load becomes stationary and predictable. So it seems possible to model and validate the aggregate load while detailed household load modelling might be difficult to treat.

Gas and electricity loads may interact to heat Domestic Hot Water and/or to provide Space Heating (SH) to dwellings. The study concentrates on residential heating demand which is mainly responsible for winter electricity peaks. So the ability of quantifying load changes from hybrid technologies is highly dependent on heating load modelling. In order to quantify the impact of each heating technology on gas and electricity load behaviours a physical description of homogenous types of dwellings is required. A literature review will guide our methodology.

1.3 Literature review

Our work can be related to planning issues. Distributed Network Operators and Transport System Operators have to forecast load evolution to anticipate network re design. This issue is common to every utility. In the article entitled ‘load prediction method for heat and electricity demand in buildings for the purpose of planning for mixed energy distributions systems’ [5] the authors propose a heat load model based on regression analyses with daily mean temperature, and statistic distribution for electricity appliances consumption. The methodology allows to assess peak loads and energy consumption for a specific area with a given composition of building categories. Regression analysis of hourly energy consumption to mean daily external temperature is also called Energy Signature (ES). A more sophisticated ES model is found in [6] to model aggregate cooling load. Explanatory variables are: diffuse radiation, direct radiation on vertical surface, specific humidity and temperature; thus multi linear regression techniques are applied. Building inertia has not been modelled because it has a second order effect on daily cooling loads. On the contrary, heating loads are concerned with inertia for areas with high thermal mass buildings. For instance in France, daily gas load profile models use a smoothed temperature to account for delay effect. Such statistical analysis relies on metered data and is not able to model gas or electricity loads from various systems. Such limitations are highlighted in [7] and [8]. They recall us the inability of top-down approach (for large scale area) in dealing with new technologies and physical factors in buildings, and the necessity of setting up an Engineering Bottom-Up model.

Instead of statistical methods, engineering methods are the only way to study the impact of one technology to another on loads. Engineering Bottom-Up Models are based on three techniques: Distributions, Archetypes, and Sample, see [7]. The last is data intensive, so the applicability is limited, and the first does not really apply for our intention which is only SH. Thus we will concentrate on archetype method which consists in few homogeneous groups of building that can be characterised with physical parameters. In [8] bottom-up models for simulating a building stock are reviewed. All those models are intended to calculate energy consumption annually or monthly. Detailed simulation of space conditioning loads have been conducted by Huang and Brodrick [9] with 144 hourly simulations of residential building with the DOE-2.1E program. They concluded that the estimated energy consumption with the bottom-up model matched with top-down statistical approach, and that detailed hourly load shapes could be useful to develop energy services contracts. But no hourly, or daily, load validation is proposed.

Reviews pointed out that the major drawback of Engineering Bottom-up Models is the assumption of occupant behaviour [8] [7]. Besides, indoor temperature is a key parameter for space-heating consumption and is often unknown and unmeasured. Based on a validated survey of 923 households, Cayla et al exploited a database with technical, weather, energy practices, and socio-demographic variables describing each household, [10]. A multi-regression analysis shows that 50% of the space heating energy variance is explained, with a proportion of 66% for technical-environment and 33% of socio-demographic and energy practices explanatory variables. This finding is consistent with other studies and proves that SH demand on an individual dwelling scale is largely dependent on non-physical parameters.

Another similar issue has been raised by electricity utilities, the Cold Load Pick Up problem. After an extended power outage in winter, Distribution Network Operator has to quantify the magnitude of the load supplying heaters once the current is back on. Those issues are more relevant for a small area but still the heating load dynamic has been faced. For instance in [11] the authors generate electrical load for a thermostatically controlled heating with an equation with two components, C, the building thermal mass in kWh/°C, and G, building equivalent thermal conductance in kW/°C.

This simplified model, a one order model, is widely used for cold load pickup prediction applications, in [12] as well. The methodology is quite similar to an Engineering Bottom-up Model with a need to obtain physical description of dwellings with limited inputs for a realistic aggregate load. In [11] all parameters came from state agencies and questionnaires, and in [12] they came from Hydro Quebec and tuned to match the load characteristics for each utility (mean, and standard deviation):

- G = 1/R, mean building equivalent thermal conductance, kW/°C;
- C, mean building capacity, kWh/°C;
- Thermostat deadband, °C;
- Mean thermostat high point during the day, °C;
- Mean thermostat stepoint during the night, °C;

Validation is done with comparison of actual feeder load to model output.

Although the aggregation modelling is similar to our aim, this approach does not suit to our objectives because it is too dedicated to power prediction and is not consistent with yearly space heating demand. A more realistic building model is compared with field test data by Savery and Lee

[13]. The use of 2 capacitances and 3 resistances, a third order building model, revealed to be satisfying to model the long and short dynamics.

Focusing on the building model itself, we refer to the publication of Bacher and Madsen [14] who compared few model structures for building identification process on an experimental building: from a simple model of 3 parameters, equivalent of the one-order model of [12] and [11] (except that solar radiation is included), to a 10 parameter model with a much higher degree of complexity. The main inconvenient for our interest is that the test building has lightweight outdoor walls. Indeed, it is known that the complexity of the model is dependent on the structure of the housing. For instance, lightweight constructions have low thermal inertia and the number of nodes required in walls can be lower than thick brick wall buildings for finite difference calculation. In [15], Fraisse et al studied the impact of the number of elements on the transient heat transfer on a wall composed of 8 cm exterior insulation and 16 cm concrete. They compared few arrangements of nodes within the wall, and different model order, and they show that wall responses are distorted with the number of node temperatures. A good agreement seems achieved for 3R2C wall models; higher orders do not provide significant improvement regarding our issue.

The structure of the building model varies with the objectives of such models. Yet there is a common feature, the buildings are represented with a unique inside temperature for a mean room of the building, in other words mono-zone thermal simulation. This assumption means that the representative building temperature is a weighted temperature of all rooms.

From this analysis it is clear that our goal is in the middle of different disciplines, utility short load dynamic models and large bottom-up models validated in energy. The review highlighted the need of:

- A detailed database of physical building characteristics for a fine spatial mesh;
- Simplified building model representing thermal inertia, consistent with the objectives;
- Realistic inputs to model a realistic load behaviour, weather and gains;
- Statistics on heating energy practices to reduce uncertainties.

1.4 Objectives

Our goal consists in assessing electricity and gas load changes from hybrid gas-electricity heating systems. This work is ambitious because validation at a regional scale is directly dependent on the amount of data available (at the desired resolution). To ensure the consistency of our method we need to set realistic objectives. The whole model should have a part of prediction ability (meaning that it is able to represent real load behaviours), with some admitted uncertainties, and valid with Space Heating (SH) needs from top-down approach. For instance it would be unrealistic to validate hourly space heating load profile at large scale because the true profile does not exist; because aggregated with other end-uses. In addition, input parameters should be consistent with the validation step, a large set of input variables might be useless, and instead a focus on determinant factors is more relevant. Real local weather data are compulsory for any validation purpose. Even if available, uncertainties introduced with uniform temperature field within a mesh will remain.

System performances are also part of the validation process. As it is impossible to model the real system operation at minute time steps, an hourly load is enough to obtain a good agreement between model and real systems (see section 2.6). So it seems feasible to evaluate system performance at an hourly resolution, while the load itself is validated at a daily resolution. Our model has the ambition to be consistent with conventional bottom-up model.

Our objective is to model daily gas and electricity loads of dwelling heating demands at a regional scale. The finer mesh of the model is about 5000 km² (mean area of French department) and regions have an average area of 25000 km². The finer mesh decision is justified, first because the amount of data available allows it, and secondly because further refinement would imply too much data compared to any potential improvement.

Even if it seems difficult to assess the results' validity, with such objectives we will be able to quantify the impacts of hybrid gas-electricity systems based on a likely load. Then with scenarios of deployment of technologies, we will be able to appreciate the effect of those technologies. Gas and electricity daily mean power of the residential sector will help planning decision issues.

2 DYNAMIC BOTTOM-UP LOAD MODEL

2.1 Methodology

The methodology applies an Engineering Bottom-Up Model with dynamic features. As in a conventional model, we employ a detailed building stock database consistent with heating demand factors.

Space Heating demand is dependent on many parameters illustrated on Table 1. All variables are considered in the model except those in italics. The impact of wind and nebulosity are second order effects while temperature and irradiation are first orders. Relative compactness and shape factor are included in the building archetype description. Window and door openings are difficult to deal with. Permeability is not taken into account directly but included in ventilation rates.

Table 1- Space heating determinants

<table>
<tr><td>Weather</td><td></td><td>Temperature
Solar irradiation
Nebulosity (sky radiation)
Wind</td></tr>
<tr><td rowspan="3">Building design</td><td>Morphology</td><td>Relative compactness
Shape factor (characteristic length)
Surface
Glazing area, window to floor area
Orientation</td></tr>
<tr><td>Materials</td><td>sensible storage
Average U-value, opaque and window
Permeability</td></tr>
<tr><td>Operation</td><td>Ventilation, air change</td></tr>
<tr><td rowspan="3">Occupancy & Behavioural factor</td><td>Internal gain</td><td>Specific electrical demand
Human metabolism</td></tr>
<tr><td>Comfort requirements</td><td>Temperature Settings
Thermostat setback</td></tr>
<tr><td>Building usage</td><td>Window, door opening</td></tr>
</table>

At this stage, the model has to include:

- Local weather data, temperature and irradiation recorded in the biggest city of a department ;
- Detailed housing stock description of the departments;
- Thermostat setting profiles
- Internal gains due to occupants' body heat and electrical appliances

The last two modules are the most uncertain parts. They have to be realistic with enough diversity to have a chance of representing accurately the aggregate load. Few scenarios for both would not be realistic and consistent with our method.

Regarding the performance of heating equipments, calculation of thermal needs is done with an hourly resolution in order to evaluate part loads. Yet the accuracy of aggregate load at an hourly time step is questionable.

Validation

Validation is the most difficult part of this research and not achieved yet, first because regional loads are not public, but also because the methodology to apply is not straightforward. The aggregate load is composed of different sectors than the residential one, which is a major limitation. Yet we can focus on prediction models to extract information on the aggregate load properties, especially on weekends and on Sundays while the tertiary sector is supposed not to affect the global load. First, both in electricity and gas, the temperature is smoothed to take into account building inertia. This operation can be processed at hourly or daily time steps. Secondly, another effect is predominant, the effect of cloud cover which prevent housing to be heated from solar radiation (at least in France). As presented in [16] the nebulosity interacts with the smoothed temperature to define an external equivalent temperature; modified by building physics. In others the wind is also considered as an exploratory variable, but such level of detail is out of scope (also because our study focuses on France).

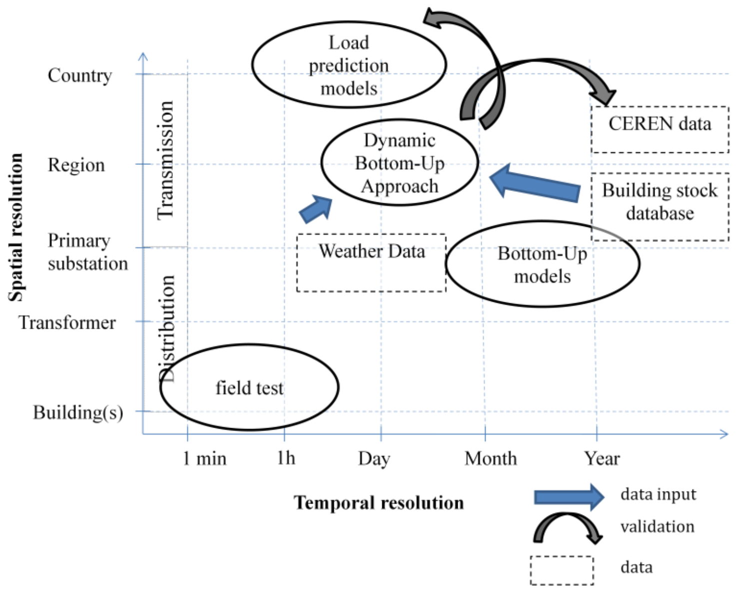

Figure 2 - Spatial and temporal resolutions of model and data

To comply with thermal aggregate load prediction models at short time steps, our bottom-up approach has to include solar radiation and building inertia effect. That is why we consider large scale thermal dynamic simulation. This model will have the following characteristics:

- Be consistent regarding to annual space heating consumption, for each element of the building stock segmentation;
- Have similar aggregate load properties.

So the validation procedure, presented on Figure 2, will be done in two steps:

- Compare annual heating energy consumption [17] at regional scale for each segment;

- Daily load variations in winter over a month to check the load dynamic. Assuming that all energy usage are constant from one day to another (for same day types), and particularly that within a few weeks lighting needs can be considered constant. It is possible to check that load dynamic is similar to the modelled one. The load dynamic is characterised by the thermal-gradient and a smoothed temperature [16]. Unfortunately, the lack of regional data does not permit any comparison with metered loads.

Detailed thermal building simulation requires a large amount of input data. Such details may be gathered for a case study which is focused on a limited area and for few buildings. Yet, in accordance with our goal (focusing on daily variation) we will develop a simplified dynamic model that can run rapidly on a personal computer, with a limited number of inputs.

2.2 Building stock description

Data description concerning energy source (gas, electricity, fuel oil, biomass…), location (regional or departmental distinction) and construction year of the building are worked out by Energie Demain (engineering consultant specialised in energy demand of buildings) based on French National public statistics institute (INSEE) population census (year 1999). Energie Demain completed this characterization of the building stock with physical depictions of the different architectural types (with a typical plan and measures) and construction materials originally used when the building was constructed. Energie Demain estimated the thermal renovations that have already been carried out according to the architectural type. We used parts of Energie Demain's database for our study.

The decomposition of the building stock we retained is as follows, for different 11 types of houses:

- Energy;
- Gas
- Electricity
- Vintage, year of construction :
- before 1915
- 1915 - 1948
- 1949 - 1967
- 1968 - 1974
- 1975 - 1981
- 1982 – 1989
- 1999 -2005
- after 2005
- Main material of walls

And for each segment the following parameters are provided:

- Floor area
- Wall area
- Wall U-value
- Roof area
- Roof U-value
- Rate of fenestration
- Window U-value
- Ventilation rate

In total, there are 65271 segments for all heating energies and 17603 describing electricity and gas heated dwellings. According to INSEE, there are 8.5 million electricity and gas heated single-family houses in France.

2.3 Weather data

Both real temperature and solar radiation profiles are acquired. The resolution of temperature is 3 hours whereas global horizontal radiations are defined at a 1 hour time step. Temperature profiles come from Meteo France weather station in 47 locations covering France (mainly around big cities). For hourly calculation purpose, temperature profiles are interpolated linearly. Global horizontal radiation profiles are provided by Armines through their service SODA (Services for Professionals in Solar Energy and Radiation). These profiles are available for few cities.

Solar profiles have to be treated to assess solar radiation on vertical surfaces oriented toward north, south, east and west and adapted to local time. The algorithm presented by Kreider and Rabl [18] and applied here follows the steps:

- Transform Universal Time into solar time using the equation of time; and also generate local time values including day-light saving time.
- Calculation of the zenith angle and the azimuth angle, and then the incident angle of direct solar radiation on vertical planes
- To distinguish diffuse and direct radiation we use the correlation established by Erbs, clearness index and extraterrestrial irradiance are computed internally, with the underlying assumption of isotropic irradiance.
- Global irradiances on vertical surfaces are assessed with a typical ground reflectivity of 0.2
- Finally using typical transmittance coefficient of double glazed windows, coupled with a correlation for considering the impact of reflectivity, found in [19], we compute the transmitted irradiance into the building

The amount of solar irradiance transmitted to the building is then calculated with the rate of fenestration on each orientation (north, south, east and west). The breakdown of fenestration surface is unknown on each wall, but is supposed to be higher on the south side of households. The influence of solar radiation on the walls is neglected in this study. Only the south wall is affected by a sol-air temperature which can be considered to be a second order effect.

2.4 Building model

As already noted, we need to represent thermal inertia and solar heat gain to be consistent with prediction model. Building stock bottom-up simulation requires a large amount of simulation to calculate individual loads of homogeneous groups of dwellings. To do so, we need a validated simplified thermal model than is able to run quickly on personal computer, and avoiding the use of detailed building simulation program requiring detailed description. The first assumption is that we will consider only monozone simplified models, meaning that indoor temperature is uniform in all rooms.

The methodology consists in computing each thermal load for each segment.

The literature provides few models but it seems more consistent to work on a validated model. The following model has been tested and validated by comparison with TRNSYS type 56:

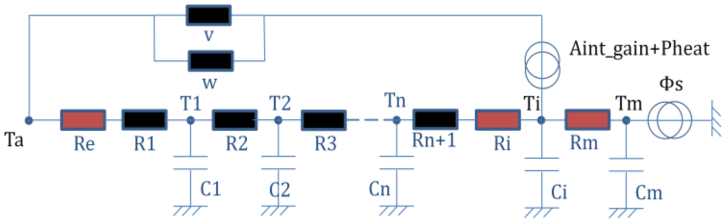

Figure 3 - Building model representation

With:

- Ci, internal capacity of air and furniture (J/°C);
- Cm, capacity of an equivalent mass of floor (J/°C);
- Cj, j ϵ [1,n] capacity of the outdoor wall (J/°C);
- Rj, j ϵ [1,n] resistance of the outdoor wall (W/°C);
- Re, external convective heat resistance (W/°C);
- Ri, internal convective heat resistance (W/°C);
- Rm, resistance between mass and internal node (W/°C);
- v, inverse of ventilation losses (W/°C);
- w, window thermal resistance (W/°C);

Red components of Figure 3 are fixed whereas black ones vary with the building. Tj ϵ [1,n] are internal variables equally spaced in a wall. Only one wall is considered to represent the dwellings envelop, required to model building inertia.

Represented as conventional Linear Time Invariant, with n+2 state space variables:

$$\begin{cases} d\boldsymbol{T} = \boldsymbol{AT}dt + \boldsymbol{BU}dt \\ T_i = \boldsymbol{CT} + \boldsymbol{DU} \end{cases}$$

$$U = [T_a, P_{heat}, \phi_s, A_{int}]^T$$

P_{heat} is a binary variable equal to 0 or the installed heating power capacity {0, Pinstalled} controlled by a static thermostat dead-band around a set temperature (constant or with setback), same as [11] and (Lefebrve, 2002). Here the thermostat dead-band is narrow to be as close as TRNSYS, which calculates thermal needs. We neglect the sensor time constant which is in the order of minutes. A_{int} and Φ_s are internal gain and solar gain. The calculation is then processed with a one-minute time step and summed at hourly time step.

The model has been validated with TRNSYS with solar radiations, to check the physical consistency of heat transfer phenomenon. In fact, radiation heat transfer is not modelled. The methodology is the following:

Generate house model with TRNSYS with different conductivity and heat capacity for the one-layer outdoor wall (9 cases). The test case is a 100m² houses with one level, 13% of windows and an insulated roof. Window properties and ventilation rate are kept constant. The computation of the heat load for each building for three weather data for two heating regimes: constant indoor temperature and thermostat setback, so 54 cases in total. Ground heat losses are ignored in this case, as it brings disturbance to daily variations. Further refinement would not bring benefits to our study. Wind speed is ignored. In addition, sky temperature has been set equal to the ambient temperature, again to study the accuracy of comparable models.

Then 4 variables are adjusted to comply with the real physics of the building (radiation heat transfer, sol-air temperature…):

- Exchange coefficient, multiply Re, Ri, Rm
- Solar coefficient, multiply Φ_s;
- Mass coefficient; multiply Cm
- Window, roof coefficient; multiply v + w.

In real cases, the mass Cm in a building is difficult to assess. Here, in the model, Cm equals the area of the building times the capacity of a 5 cm thick concrete slab. Φ_s is the transmitted gains through the windows from solar irradiation. Optimal values for each 54 simulations are calculated with a minimisation of The Root Mean Square Error, and a quadruplet has been chosen to prove that the model is robust to physical properties and climate. In Table 2, we present the errors: usually Mean Average Percentage Error (MAPE) is used but when values are equal to zero, the MAPE tends to infinity. So we define the Mean Average Relative Error (MARE) which is similar to the previous one, but robust regarding zero values. The MAPE can be computed with hourly or daily profiles.

$$MARE = \frac{\sum \left|P_i - \widehat{P_i}\right|}{\sum P_i}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{\left|P_i - \widehat{P_i}\right|}{|P_i|}$$

Table 2- Error betwen model and TRNSYS

MARE	Lille	Nice	Trappes
Hourly	5.36%	11.17%	5.81%
Daily	2.16%	2.92%	2.01%

Daily load profiles have low relative error compared with hourly loads because hourly errors are aggregated within a day. We can notice that the climate of Nice, Mediterranean city, is less favourable to the accuracy of the model. Indeed solar irradiation is higher in Nice than in Lille and Trappes and the influence of the sol-air temperature disturbs the simplified model. From Figure 4 we see that heat load dynamic from the model is consistent with the simulated thermal load of TRNSYS.

Yet we conclude that the developed model satisfies our requirement, it includes:

- inertia phenomenon, represented with N nodes in the wall;
- solar effect;

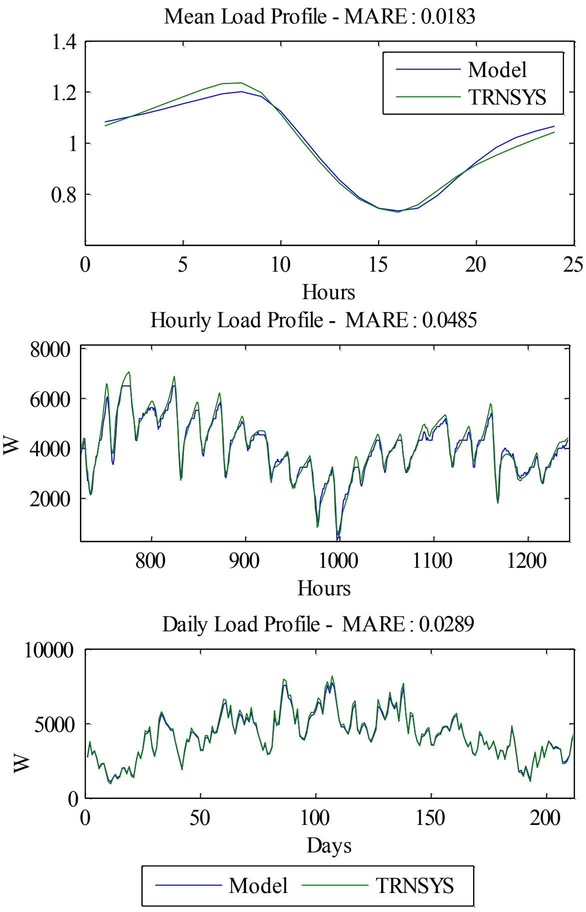

Figure 4 - Comparison of load model and TRNSYS

2.5 Internal Gains

In conventional simulation, occupation and internal gains are determined according to a conventional scenario and reference values. Yet for an aggregation model, it would not be representative to use only one or few scenarios. Then the question is what scenarios and how many ? Sophisticated stochastic modelling of gains could be a way to generate multiple heat gain profiles. However, for sake of simplicity we will use a database of 116 specific electricity profiles plus scenarios of occupiers' presence. The database comes from records of electricity loads from dwellings and flats in France. Those profiles include all standard electricity usages apart from Domestic Hot Water and Space Heating. In a first order it seems relevant because electricity use is correlated with the activity in dwellings, so it is a mean to represent the dynamic heating gains fairly well as a non-stationary and random process. However, only a fraction of this load might be transferred into internal gain in the building; washing machine and dishwasher reject hot water in the sewage which is the major limit. Figure 5 shows one internal gain profile for a week, and the aggregate internal gain load profile. The main advantage of this method is that the individual loads have the right property, they are able to be consistent with aggregate electricity load profile, in other words: what would see an aggregate dwelling.

So, 116 hourly profiles of internal gain are injected in the building model randomly. In a first attempt it seems right but internal gain load profile should be selected in accordance with the type of houses. Based on statistical analysis from household energy survey it would be more consistent to select a level of internal heat gain relative to the surface of the dwelling. However, such statistics are not available now.

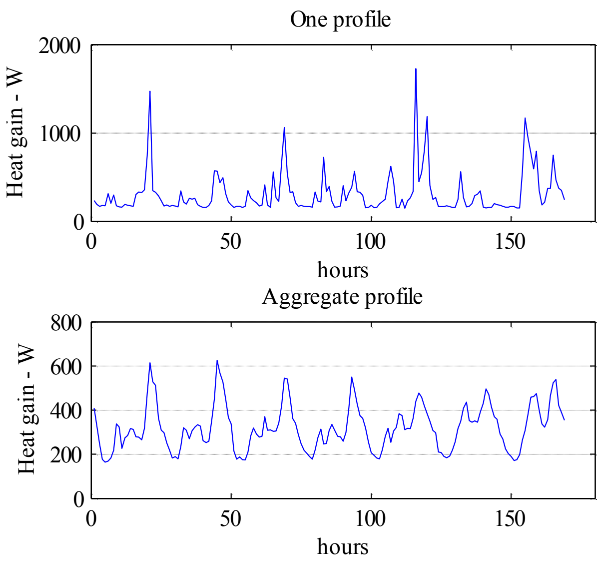

Figure 5 - Heat gain load profile in winter

2.6 Systems

System efficiencies require attention to model aggregate electricity and gas loads. From thermal load, we need to create a function that transforms hourly SH needs into energy consumption of hybrid systems. Yet, it is common knowledge that nominal system efficiencies and seasonal efficiencies might be very different. The factors affecting seasonal performance are:

- The design of the distribution mean : radiator, slab, temperature levels;
- Maintenance of the distribution, by ensuring that fluid flow rate is not decreased by fouling ;
- The sizing of the heating system ;
- Efficiency of the systems at full and part load condition.

Today, we can access full load performance from manufacturer, and part load efficiencies for standard conditions. Yet the accurate modelling of individual heating systems is nearly impossible, the behaviour of sensors and regulation rules is subjected to many disturbances. So the calculation of energy consumption at hourly time steps seems the only way, and relevant according to the literature.

In [20], the authors propose a modelling approach of part load factor that suits on-off cycle machines and modulating machines. With 3 three test points it is possible to obtain the relationship between part load ratio and part load factor. The determination of Coefficient Of Performance, COP, (for heat pump or boiler) at full load are computed with piecewise function, dependent on the start or return temperature of heating loop. Before, the regulation has to be chosen: constant start temperature, or Outdoor Compensated Temperature. The COP at partial load is computed and the electrical load is then calculated. In case the installed capacity is not sufficient to produce enough thermal power, a back-up system is launched. In [21] µCHP performances of various technologies are tested and reported. Reciprocating internal combustion engine and Stirling engine are reviewed by the authors and offer a complete analysis of µCHP efficiencies at full and part loads. All these data will be implemented in the model.

The downside of such approach is that knowledge of installed systems in the building stock is very limited. To remediate, conventional seasonal performance agreed by the industry can be found in the performance audit of applied to existing households. Those values are implemented in first simulations to check annual energy consumption from Space Heating Demand, for example in calculation models used for building thermal regulation compliance.

2.7 Behavioural variables

Energy practices in dwellings have a strong influence on SH demand, as seen in the literature review. Yet, surveys on temperature management are far and few between. In [12], statistics on thermostat settings during day and night and thermostat dead-band are collected from local survey.

In our approach, the behaviour of the occupants will be a variable (mean heating temperature of the dwelling and use of a thermostat to reduce temperature in some time periods), to adjust annual space heating consumption. Then the consistency of the overall model is discussable regarding those variables.

Socio-demographic variables are not included in our bottom-up approach due to a lack of knowledge but each segment actually modelled could be disaggregate with sub-groups including details on energy practices. Further developments are required to obtain statistics on energy practices in order to give more strength to the bottom-up model.

3 CASE STUDY

To illustrate potential results of the developed model, we will consider a region which includes 900 000 dwellings for the heating season 2005/2006. For this period, we have:

- Detailed physical description of the building stock, 700 segments representing 165 000 gas heated homes and 365 000 electricity heated homes
- Hourly profiles of temperature and solar radiation in four locations of the region;
- Annual Space Heating energy consumption for gas and electricity for homes per vintage [17];
- Internal heat gain profiles;
- Conventional seasonal performances of existing heating systems.

3.1 Comparison of model and data for year 2006

As a first shoot, the calculation of heating load profiles are processed with the simplified load models with constant thermostat settings. Figure 6 and Figure 7 present energy consumption from the bottom-up model and from CEREN. Figure 6 presents some part of extra energy consumption (in addition of electricity) that can be associated to wood from fireplaces. The portion of wood is extracted from CEREN database and the same portion is applied to the model (as it cannot be modelled, or integrated in the behaviour component). To obtain those values, thermostat settings have been artificially modified to make the bottom-up calculation match with CEREN data, those values are reported in Table 3. This artefact seems compulsory since the annual gas and electricity consumption are quite uniform through all vintages. Indeed, since 1975 thermal building regulations have imposed minimal performance of building design. Surprisingly the consumption has not decrease drastically since 1975, instead we assume the level of comfort is higher. Another explanation is that thermal performance of old housing has been underestimated in the calculation model.

Table 3 - artificial thermostat temperature (in °C constant temperature for the whole surface of the dwelling)

Vintage	**Gas**	**Electricity**
-1915	13	13
1915 - 1948	16	13
1949 - 1974	17	16
1975 - 1981	18	16
1982 - 1989	20	20
1990 - 1999	20	20

1999 +	20	20

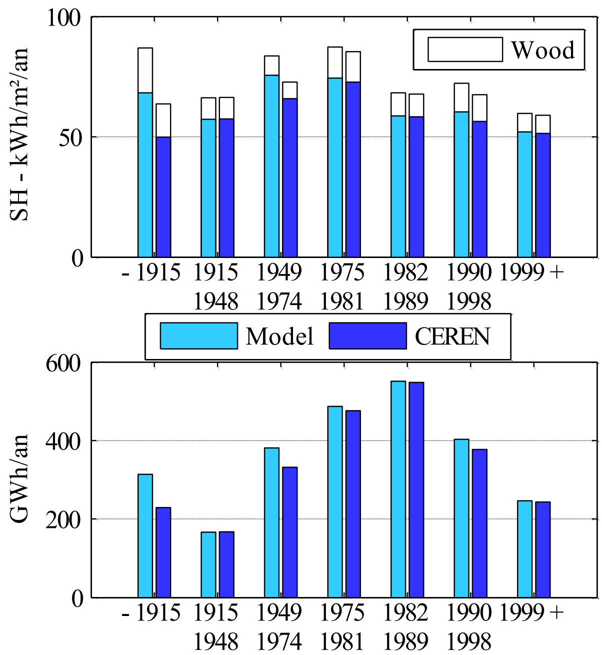

Figure 6 - Electricity consumption for heating

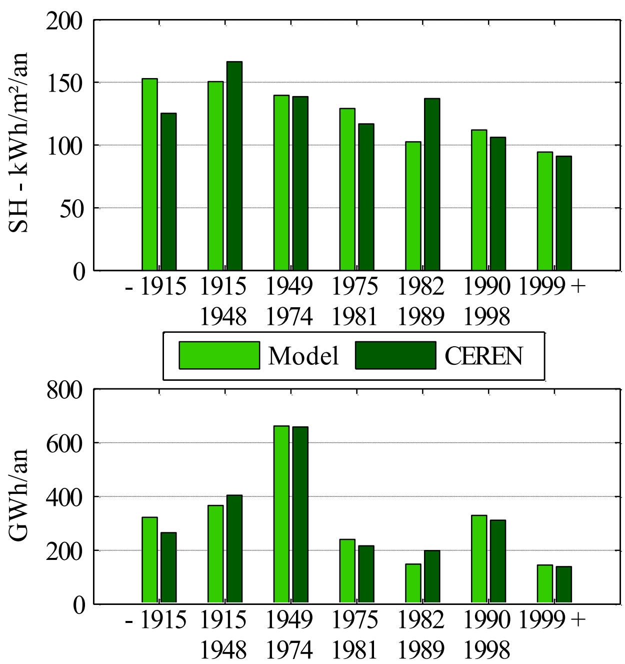

Figure 7 - Gas consumption for Space Heating

3.2 Insertion of hybrid heating systems in electricity heated building stock

Once the bottom-up model is validated with annual energy consumption, we can claim to study the impact of hybrid systems on gas and electricity loads. In a hypothetical scenario, we assume that 20% of electricity heated households are replaced by 10% of hybrid heat pump systems and 10% of µCHP Stirling engine. This scenario does not intend to be realistic or in accordance with any prospective study, it is purely illustrative.

From Figure 8, the previous computed aggregate electrical load from of electricity heated home is plotted as it is in 2006. Then, 10% of Hybrid Heat Pump and 10% of micro-CHP are inserted randomly in the electricity heated dwelling stock and the aggregate electricity load is plotted on the same graph. With this chart, we observe the discrepancy between the 2006 electricity load, with a daily peak load of 1500 MW, and the modified load from the introduction of 10% of Hybrid Heat Pump and 10% of µCHP. With such assumptions, a peak load reduction of 21% is measured. Hybrid Heat Pumps have been implemented to switch to gas consumption only below 7°C. The breakdown of the electricity load behaviour for each hybrid technology is illustrated on the lower part of Figure 8. We notice that, at peak load conditions, hybrid heat pumps do not consume any electricity whereas micro CHPs produce more than 20 MW. This illustrates the potential peak load reduction leverage obtained by replacing electrical heating systems with hybrid gas systems. In this case, we assume that the amount of wood to heat dwellings remains the same even if the system is changed.

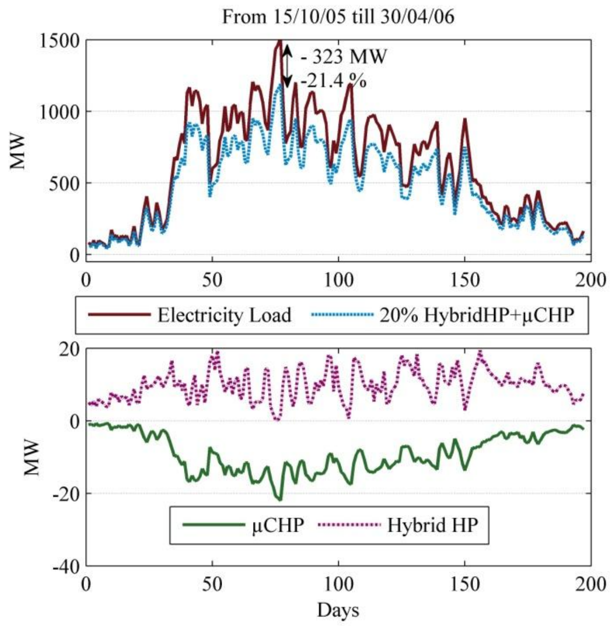

Figure 8 - Aggregate electricity loads (upper plot) and breakdown per technologies (lower plot)

On the other hand, gas peak load is expected to increase due to a higher number of consumers. On Table 4, we compare the peak and the total energy of gas and electricity load. It is interesting to notice that the gas peak load increases significantly in order to relieve electricity network. Thanks to hybrid systems the electricity peak is reduced by 21.4% whereas the electricity consumption decreases less, 19.8%. So the interaction of gas and electricity loads can relieve a network and constraint another. This duality is represented on Figure 9, for current situation and modified loads, the Energy Signatures of aggregate gas and electricity loads are plotted. For each signature, the load gradient in MW/°C and the balance temperature in °C are printed. The electricity gradient decreases from 71 to 55.4 MW/°C, whereas the gas gradient increases from 67.3 to 88.7 MW/°C. Thus, it shows that gas peak load increases from 1400 MW to 1816 MW. Therefore, integrated planning is a key point to optimise distribution network infrastructures.

Table 4 - Evolution of gas and electricity load with the scenario

%	**Electricity**	**Gas**
Energy	-19.8	27.3
Peak Load	-21.4	30.8

The ES of Figure 9 is part of the validation process of the aggregate load curve dynamic (from Transport System Operator). Indeed, for Sundays in winter, SH demand in the residential sector is predominant on other sectors and so ES of aggregate load could provide more consistency to this analyse. The value of load gradient and balance temperature could be compared to simulated ones. Unfortunately, no regional data of gas and electricity are provided at the moment.

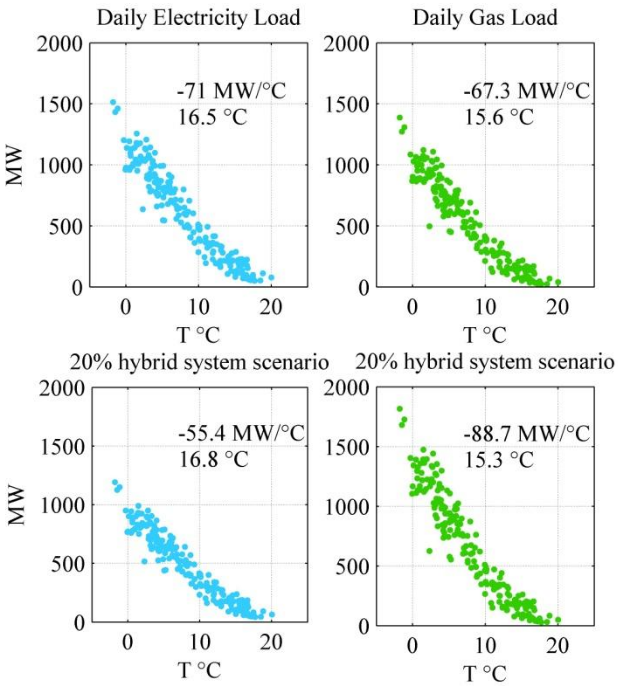

Figure 9 – Energy Signature (ES) of aggregate load for current situation (upper charts) and modified with 20% of hybrid system (lower charts). Gradient and balance temperature are printed.

4 CONCLUSIONS AND PERSPECTIVES

With this framework, we are able to simulate the impact of hybrid gas and electricity technologies at regional scale. Yet the state of development is limited to houses, and flats have to be included in the analysis to provide a complete picture of the residential space heating consumption. The overall Engineer Bottom-Up model contains every block to build and simulate a likely aggregate load, and investigate the impact of different heating technologies. Attention has been paid to develop a consistent and realistic simulation tool of aggregate load at daily time steps with an emphasis on data availability.

As mentioned, the heating behaviour of occupants is the main barrier to the validation of the model. Further studies should feed the behavioural part of the Bottom Up model to improve the consistency of the results. Sensitivity analysis should help us to orient the need for accurate data. Further development is required to investigate the aggregate load behaviour depending on input variables. Such knowledge will help to validate assumptions or to orient the modelling into other perspectives. For instance, statistical distribution of setback thermostat temperature will introduce changes on the aggregate load property, especially on intra-day load behaviour. Further research is on the way to compare intra-day electricity load and simulation.

The simulation of different hybrid technologies will be processed. µCHP technologies with different prime-movers may result in higher potential benefits that the Stirling engine presented here. From this case study, we illustrate the role of hybrid technology to decrease electricity peak load and electricity demand to a lower extent.

The developed methodology will help regional planning decision maker to consider hybrid gas-electricity technologies. Today only centralised solution (especially combined cycle power plants) are considered but demand side management with hybrid technologies deserve to be deemed too. Gas and electricity distribution network interaction will relieve electricity generation capacity and transfer high loads to the gas infrastructure which is more reliable and flexible in France than the electricity one. In addition to load management, externality study on CO2 abatement might complete the infrastructure optimisation issue. The daily resolution is also particularly well adapted to this issue.

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