Modelling distributed Power-to-Heat technologies as a flexibility option for smart heat-electricity integration

Francesco Lombardi[a], Sylvain Quoilin[b], Emanuela Colombo[c]

[a] *Politecnico di Milano, Milan, Italy*
[b] *KU Leuven, Leuven, Belgium*

Abstract:
Coupling heat and electricity through power-to-heat (P2H) technologies is raising increasing attention. It allows, on the one hand, to substitute traditional heating technologies with highly-efficient heat pumps (HPs), while, on the other hand, exploiting cost-effective thermal storage options (TES) such as hot water tanks, ultimately increasing system flexibility and renewables penetration. Nonetheless, an accurate assessment of the benefits that may be ensured by a country-wide diffusion of P2H technologies is hindered by computational difficulties in representing large numbers of distributed HPs and TES systems within regional- or country-scale energy models. In this work, we simulate large numbers of individual HPs and TES systems and compute the realistic aggregate electricity consumption associated with those. Various relevant regulation logics are simulated, either thermostatically-controlled or aggregator-controlled. For the latter, we show that an equivalent virtual power plant (VPP) representation ensures sufficient accuracy for use in large-scale energy models (NRMSE<10%). Finally, we evaluate the flexibility potential ensured by the different P2H configurations considered, by incorporating those into an open energy system optimisation model. We show that flexibility and decarbonisation benefits are achieved in all configurations, although they increase (up to -89.5 GWh/week of primary energy savings) with the degree of 'smartness' and PV-friendliness of P2H operation logics.

Keywords:
Power-to-Heat, Modelling, Heat pumps, Flexibility, Smart Energy Systems.

1. Introduction

The residential heat sector, comprising cooking, water heating, space heating and cooling energy end uses, accounts for up to 23% of final energy consumption in the EU, whilst being largely dominated by direct or indirect conversion of fossil fuels [1]. As such, it is at the core of EU decarbonisation policies, which are particularly focusing on the benefits that may be brought about by the integration of heat and electricity sectors through power-to-heat (P2H) technologies, such as highly efficient heat pumps (HPs) coupled with flexible thermal energy storages (TES) [2]. In fact, these technologies can be installed in most households with little effort, and may represent a fast option to significantly reduce the carbon intensity of the energy system while also facilitating and benefitting from increasing penetrations of renewables.

Such decarbonisation potential, however, needs to be quantitatively assessed at the country scale. Energy system optimisation models (ESOMs) are typically used to investigate changes in the configuration of the power system such as those entailed by a deep penetration of P2H technologies, and to inform energy policies accordingly. Nevertheless, a technically-accurate representation of large numbers of distributed individual HPs and TES systems within an ESOM is not trivial [3, 4]. In fact, heat demand profiles and, consequently, HPs and TES operation are unique for each independent household, resulting in heterogeneous sets of millions of dispersed loads. Conversely, ESOMs can only handle aggregate (e.g. regional) figures for such loads in order to maintain computational tractability [3].

Due to such complexities, previous work managed to explore the benefits of P2H integration only by sacrificing the spatial (e.g. focusing on a small district) and/or technical (e.g. limited accounting of the effects on the power system) scope of the analysis. For instance, Chapman et al. [5] investigate the reserve capacity that could be provided by aggregates of HPs coupled with TES, yet limiting the analysis to a district of 500 buildings. Similarly, Fischer et al. [6] simulate the flexibility ensured by different P2H configurations for the provision of domestic hot water (DHW) for a pool limited to 284 HPs. On the contrary, country-scale analyses have relied either on a spatially-homogeneous, top-down application of standard HPs operational profiles [7], failing to account for loads and technology diversity, or on bottom-up aggregations of limited sets of "representative" building or user archetypes [8], [9], possibly overestimating coincident user behaviour and hence peak demand. Moreover, large-scale analyses integrating supply-side and demand-side models have so far relied on coarse-resolution (e.g. single-region) representations of both aggregate P2H technologies and the power system [3], [8], [9], disregarding the complexities entailed by transmission bottlenecks and region-specific, weather-dependent HPs operation.

More realistic, but still computationally tractable representations of pools of P2H technologies in a spatially-explicit country-scale power system are, however, possible. This is valid for the case of both conventional P2H technologies, which operate following thermostatic control logics, and 'smart' ones, which can be remotely controlled by a so-called "aggregator" to provide flexibility to the power system. In the former case, the aggregate electricity consumption of a multitude of dispersed, thermostatically-controlled HPs in a given region can be simulated a priori for each individual technology, based on a pre-defined control logic. The resulting regionally-aggregate electricity consumption can be managed in an ESOM as an additional, spatially-explicit electrical load to be met by the power system, without flexibility. In the latter case, instead, each HP is subject to *direct load control* (DLC) by an aggregator, which manages the aggregate of all HPs as a virtual power plant (VPP) to provide flexibility to the power system. In such case, the aggregate electricity consumption cannot be simulated a priori, and the operation of several regional VPPs becomes itself an optimisation variable of the ESOM. The regionalisation of VPPs allows to carry information about location-specific and time-varying weather conditions and users' demand. Yet, this requires to assess how well the representation of an heterogenous set of technologies (HPs and TES of different sizes) as a single VPP technology with average characteristics of the set, in an ESOM, approximates the operation of a real aggregate subject to DLC.

In this work, we analyse a range of possible P2H configurations for the provision of DHW and introduce realistic, bottom-up representations of their aggregates into an ESOM, built within the Calliope modelling framework [10]. The context of application is the Italian energy system, where up to 5.6 million conventional electric, gas or other-fuel standalone DHW boilers could be replaced by more efficient P2H systems [11]. The chosen P2H configurations are:

a. conventional, thermostatically-controlled HPs;
b. solar-friendly (also known as SG-ready) thermostatically-controlled HPs;
c. smart HPs subject to DLC.

For each, we compute realistic sets of heterogenous DHW load profiles with a previously-developed bottom-up stochastic model (RAMP [12]) and, subsequently, aggregate figures for HPs and TES operation in each of the 20 Italian regions, accounting for differences in the building stock and in weather data. Hence, we use those as an input for a 20-region Italian heat-electricity integrated energy system model, which expands a previously-developed, Calliope-based and openly available model of the same country [13]. The objective of the analysis is to evaluate the impact of the selected P2H configurations on both primary energy consumption and on the power system operation, with a high level of spatial detail. For the case of non-DLC loads, we use the computed aggregate HPs consumption figures as an additional electrical load and compute the optimal operation of the power system to meet this additional load. Conversely, for the case of HPs subject to DLC, we first demonstrate the consistency of the VPP representation and hence feed the model only with the simulated aggregate DHW demand profiles, letting the spatially-explicit HPs operation become one of the optimisation variable of the model, i.e. a flexibility option, for the computation of the optimal operational strategy.

2. Methods

The three P2H configurations selected for this study are summarised in Table 1. Such configurations allow to represent increasing degrees of "smartness", all already available as features of commercial HP models or demonstrated in real-life applications [6], [14]. In particular, the *thermostatically-controlled* (TC) configuration represents the widespread fixed-speed HP models that operate continuously to ensure that a given set-point temperature (typically 55°C for DHW tanks) is maintained in the TES. The *PV-coupled* (PV-TC) configuration, instead, represents variable-speed HPs often coupled to existing domestic rooftop PV installations to maximise PV self-consumption by converting, and storing excess PV generation in the TES. Typically, such models still operate based on a set-point logic, but allow for *overcharging* of the TES, i.e. heating to a higher temperature (+5°C) than set-point, during peak PV production hours, and are also known as *smart-grid ready* (SG-ready) [6]. In this work, we assume that they can also receive signals of PV availability from neighbours in the same region, such that their installation is not constrained to owners of rooftop PV only. Such aggregation of multiple prosumers is not yet common, but might undergo significant deployment in the future, e.g. as a result of the support for 'citizens energy communities' in Europe's new electricity market design [15]. Finally, the *smart direct control* (DLC) configuration represents those models which are commercialised equipped with smart meters that allow a so-called "aggregator" to directly control the operation of the HP, simultaneously with thousands of others and without affecting users' comfort, in order to sell flexibility services to the grid operator [8]. A real-life example of this mechanism is reported by Müller and Jansen [14].

Table 1. Summary of selected P2H configurations and related operation logics.

P2H configuration	Operation logic
*Thermostatically-controlled **(TC)***	HP is *on* when T_{TES} is below set point; *off* otherwise.
*PV-friendly **(PV-TC)***	HP is *on* when T_{TES} is below set point; always *overcharge* TES when local PV production is detected.
*Smart direct control **(DLC)***	HP "smartly" turned *on* to minimise system and users' costs based on system-wide load and weather foresight.

In order to quantify the impact of these P2H configurations on the power system operation and on the overall primary energy consumption for heating, we model their aggregate load adopting a bottom-up approach. First, spatially-explicit (i.e. for each Italian province, or NUTS 3, subsequently re-aggregated to NUTS 2) stochastic DHW load profiles are computed for 56'000 independent users. This corresponds to 1/100 of the actual total number of potential users (to which they are subsequently rescaled) and is deemed sufficient to reproduce load diversity while still being computationally tractable. The profiles account for province-specific building stock information (larger dwellings have higher DHW consumption) and groundwater temperature hourly data. Secondly, we simulate an independent P2H system operation for each of these users, and for each of the three configurations. In particular, for the first two configurations, this is achieved through a thermodynamic simulation model, whilst for the DLC case we build a single-user optimisation model within the Calliope modelling framework. Finally, we integrate the computed aggregate P2H loads into the Italian 20-region energy system model for the computation of their actual impact on the operation of the power system. The following sub-sections provide further details about the methods adopted in each step.

2.1. Spatially-explicit DHW load profiles

The final consumption of DHW is influenced by dwelling size and climatic conditions (affecting groundwater temperature), but it is mostly subject to highly unpredictable user behaviour. As such, several authors noted the importance of adopting bottom-up stochastic models for its simulation [16], [17]. To that aim, we rely on the open-source bottom-up stochastic model RAMP, which was developed in previous work to generate multi-energy load profiles, including DHW, and which has been already adopted, with ad-hoc modifications, for large-scale simulations of user-driven heat demand profiles [18]. In particular, we modify RAMP's simulation logic in such a way that the randomisation of users' behaviour is also connected to spatially-explicit data about dwelling size (considering four possible geometries) and distribution, and groundwater temperature, as summarised in Fig. 1. We define four possible DHW "appliances", namely: shower, kitchen sink, bathroom sink, and generic. For each, we compute an average instantaneous thermal energy consumption (Eq. (1)), as a function of the flow rate ($\dot{m}_{DHW,k}$) and of the difference between temperature of use ($T_{DHW,k}$) and groundwater temperature ($T_{gw,d}$) – the latter given as a daily average for each province. The absorbed power is then made subject to randomisation, for each independent user and for each DHW usage event, to reproduce unpredictable user preferences in terms of flow rate and temperature. The model randomly computes timing and duration of DHW events, based on information regarding building occupation patterns, until reaching a pre-defined total time of use – again subject to a certain degree of randomisation – for each DHW appliance. Assumptions about typical flow rates and temperature levels are elaborated from the literature [16], [17], [19]. Further details about the input data are openly accessible at the dedicated repository [20].

$$\dot{E}_{DHW,k} = \dot{m}_{DHW,k} c_{p,w} (T_{DHW,k} - T_{gw,d}) \qquad (1)$$

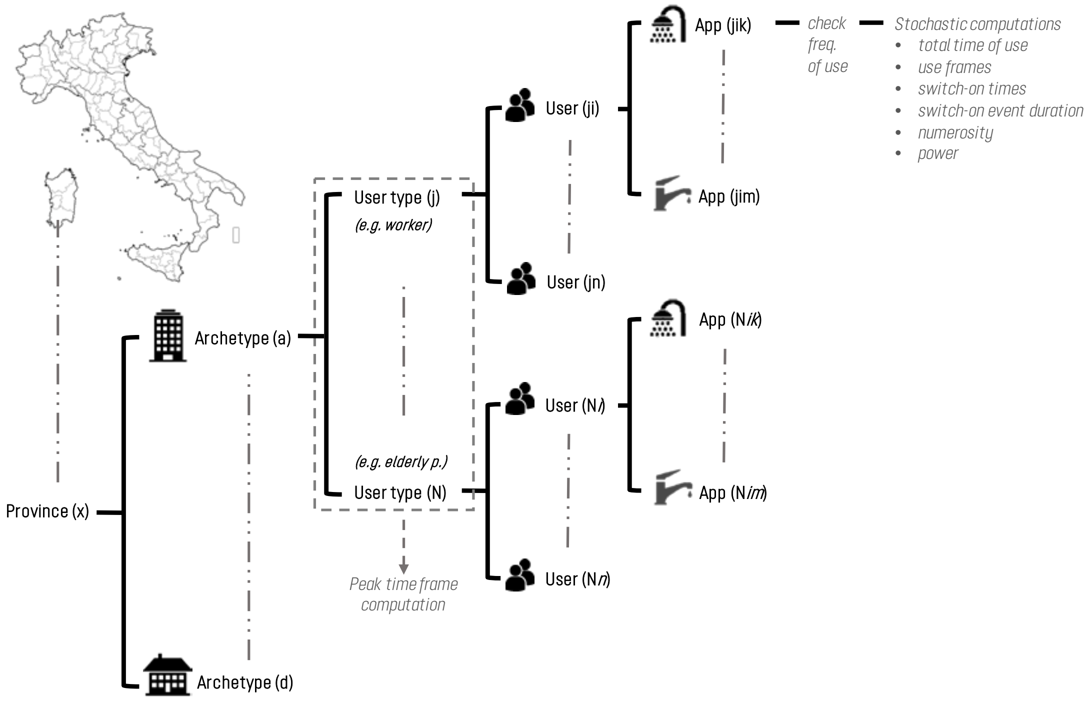

Fig. 1. Sketch of the modified RAMP simulation logic adopted for the study. Figure adapted from Lombardi et al. [12].

2.2. Simulation of P2H operation for individual users

Fig. 2 summarises the P2H system thermodynamic representation. The TES is represented as a fully-mixed water tank [21], whose state of charge in each time step is computed as per Eq. (2). Losses towards the surroundings are computed as a percentage of the state of charge ($\%loss$), and hence higher losses are experienced for higher charge (i.e. temperature) levels. The energy discharged ($Q_{TES,disch,(t)}$) in each time step is that the one needed to satisfy the load demand profile. The HP charges the storage based on the control logics defined in Table 1. When the HP is switched on, its power output is either driven by a fixed electric consumption (for fixed-speed configurations, Eq. (3)) or modulated based on the tank state of charge (for variable-speed configuration, Eq. (4)). In the latter case, whereas PV availability is detected, the HP is operated at full-load, without inverter regulation, as long as overcharging of the TES is possible. The COP dependency on outdoor temperature is computed as per Eq. (5), empirically obtained by Staffell et al. [22] comparing many commercial models.

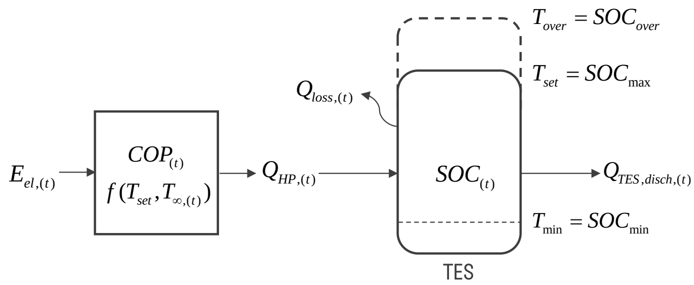

Fig. 2. Sketch of the thermodynamic representation of the generic P2H system.

$$SOC_{(t)} = SOC_{(t-1)}(1-\%loss) + Q_{HP,(t)} - Q_{TES,disch,(t)} \qquad (2)$$

$$Q^{fs}_{HP,(t)} = E^{fs}_{el,HP,nom} COP_{(t)} \qquad (3)$$

$$Q^{vs}_{HP,(t)} = \left(\frac{(E^{vs}_{el,HP,\min} - E^{vs}_{el,HP,nom})COP_{nom}}{SOC_{\max} - SOC_{\min}} \right) SOC_{(t-1)} + E^{vs}_{el,HP,nom} COP_{(t)} \qquad (4)$$

$$COP_{(t)} = 6.81 - 0.121(T_{set} - T_{\infty,prov,(t)}) + 0.00063(T_{set} - T_{\infty,prov,(t)})^2 \qquad (5)$$

2.3. The 20-region heat-electricity Italian power system

Building on previous work [13], the Italian energy system is modelled adopting a double-scale spatial representation. In particular, as shown in Fig. 3, we characterise electricity demand profiles, dispatchable power production/storage plants and inter-zone transmission lines at the bidding zone level, whilst we model renewable capacity, pumped hydroelectric storage (PHS), DHW demand, HPs and TES at the regional (NUTS 2) level. The NUTS2 level data is then aggregated to the bidding zone level for the power system simulation. It is thereby assumed that power production from renewable power plants is influenced by region-specific weather conditions, but that it converges to a central bidding-zone electricity demand node by means of unconstrained transmission lines. Conversely, P2H conversion is entirely (i.e. both DHW demand and supply) region-specific. Yet, it is indirectly influenced by transmission bottlenecks across bidding zones that constrain the utilisation of, e.g., renewable power produced in southern regions for the P2H conversion in northern regions. Electricity demand profiles for each bidding zone are elaborated based on data gathered by the Italian TSO [23] and Open Power System Data [24]. Power plants capacities, efficiencies and costs are taken from previous work [13], and openly accessible via a dedicated repository [20].

2.4. Metrics for results interpretation

The accuracy of the VPP representation for the P2H-DLC case is tested by evaluating the *Normalised Root Mean Square Error* (NRMSE), as applied in a previous study by Lombardi et al. [12] for the purpose of time series comparison. In addition to the NRMSE, the shape of the P2H electricity consumption and TES state of charge profiles is graphically compared to detect possible operation-relevant differences.

The effects of the three proposed P2H configurations on the Italian power system are measured in terms of: i) ramping costs of dispatchable power plants; ii) total primary energy supply. Considering that the model is based on a LP formulation, ramping costs are computed a posteriori as the aggregate of hot, warm and cold start-up costs and ramping costs themselves, in EUR/ΔMW. Total primary energy supply (TPES), comprising both power and heat sectors, is computed considering that DHW would be otherwise produced, in the baseline scenario, by standalone gas boilers with an average efficiency of 84% [25].

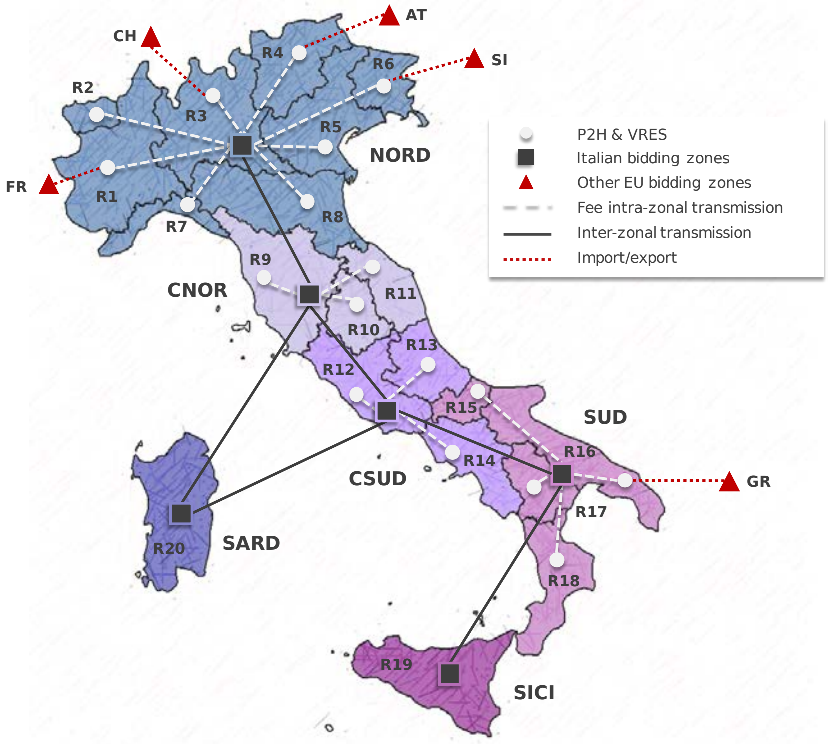

Fig. 3. Modelling representation of the Italian heat-electricity energy system. Adapted from Lombardi et al. [13].

3. Results

3.1. Spatially-explicit stochastic DHW profiles

The simulation of 56’000 independent DHW demand profiles ensures a high load diversity, as reported in Fig. 4 for the example of the 3677 profiles for the region Tuscany. For validation purposes, considering the lack of metered data for the Italian national DHW consumption profile, we check that the simulated profile has a peak-to-baseload ratio (from 4 to 6) and average daily consumption (6 to 8 kWh/day) in the range outlined by a recent review of DHW profiles for similar contexts [26].

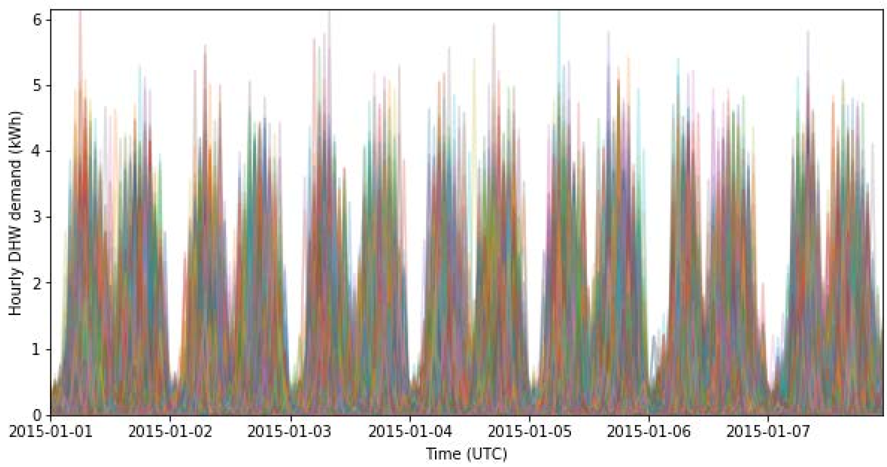

Fig. 4. Example of simulated stochastic DHW loads for 3677 independent users in the region Tuscany.

3.2. P2H individual and aggregate consumption

The results of the simulations for the different P2H configurations satisfying the same loads highlight significant differences between the conventional TC configuration and the smarter PV-TC configuration, as reported again for example region Tuscany in Fig. 5 and Fig. 6, respectively. In the first case, HP aggregate electricity consumption is very similar to the associated aggregate DHW demand profile (scaled as a function of the hourly COP). In the second case, however, the HPs individual and aggregate electricity consumption profiles are highly correlated to PV yield, with the correlation becoming stronger in regions where the solar resource is more abundant. In such regions, TES tends to be frequently fully overcharged before the end of the PV production period, leading to possible problematic steep-ramping of power plants due to abrupt PV output that is no more self-consumed and hence fed to the grid. The impact of this phenomenon is further discussed in sub-section 3.4, also considering that the peak electricity consumption in the PV-TC configuration is up to 3 times higher than for the TC case. For the DLC case, finally, the similarity in the operation of individual and aggregate P2H is even more marked, as shown in Fig. 7. In fact, in this configuration individual users have not only a signal about the availability of PV power, but also knowledge of the available system-wide capacity they can exploit – more precisely, each user "sees" an identical fraction of the regional PV capacity. As such, they operate their P2H system also taking into account that the system-wide PV capacity is not unlimited, which increases the similarity in operation across different users. This supports the idea that a VPP representation is well suited for this kind of operation logic, as further discussed in sub-section 3.3.

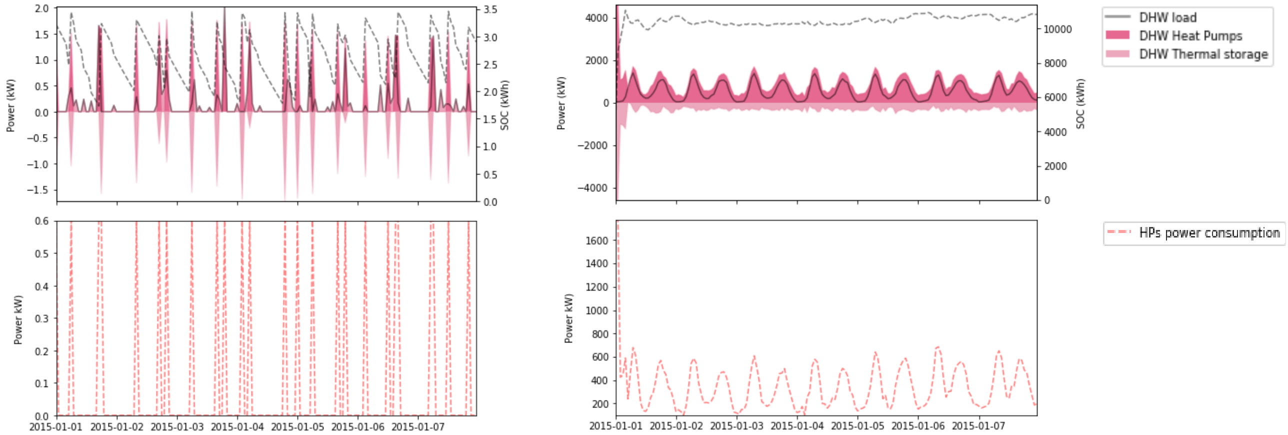

Fig. 5. Example of individual (left) and aggregate (right) TC operation of P2H for the region Tuscany.

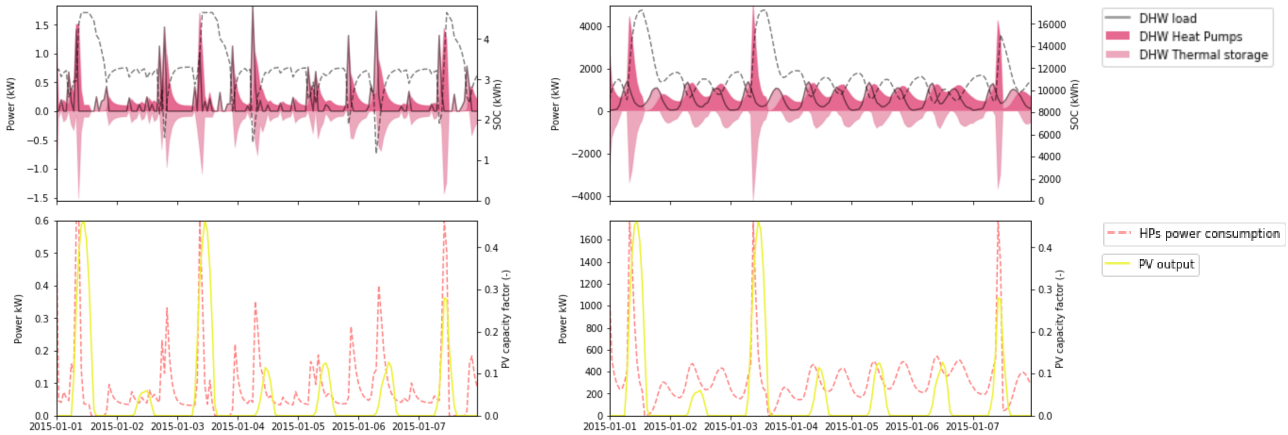

Fig. 6. Example of individual (left) and aggregate (right) PV-TC operation of P2H for the regions Tuscany.

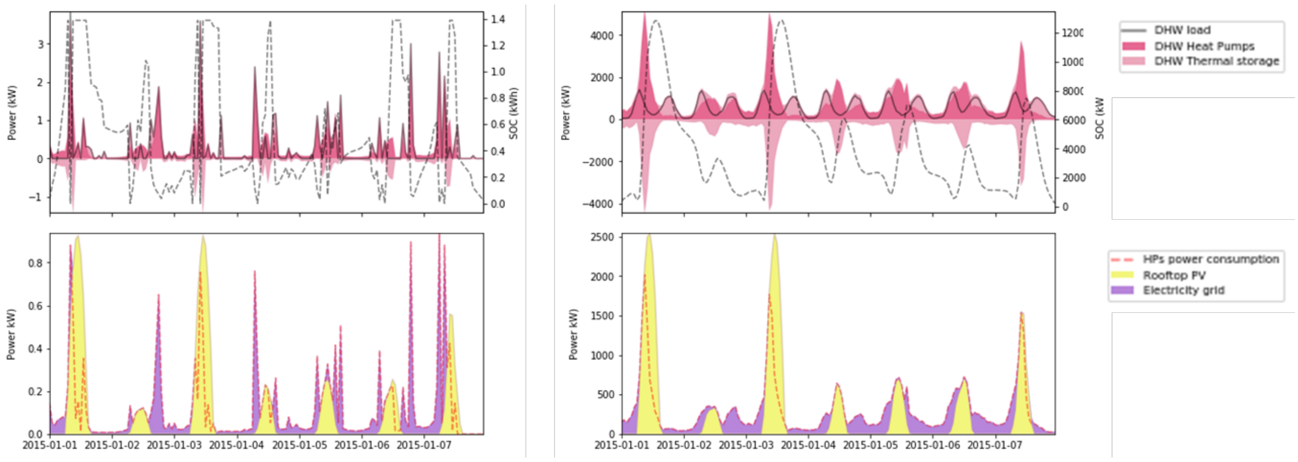

Fig. 7. Example of individual (left) and aggregate (right) DLC operation of P2H for the region Tuscany.

3.3. Accuracy of Virtual Power Plant representation

For the case of the DLC configuration, which, as previously discussed, is treated as one VPP in each of the 20 regions of the Italian energy system, we check the difference in P2H aggregate electricity consumption and in the TES state of charge between the realistic aggregate of thousands of users in each region and their VPP-equivalent representation. It is worth noting that each regional VPP is formally equivalent to a single user whose HP and TES capacity is the average of the whole set of users' for that region. Fig. 8 shows that the VPP representation provides an accurate (NRMSE < 10%) representation of the P2H aggregate hour-by-hour electricity consumption in all regions. Conversely, for the case of the TES state of charge time series, a few regions exhibit a NRMSE up to 15%, despite most of them being consistently below 10%. The difference however remain limited and do not to entail significant operational discrepancies, as shown in Fig. 9b: a difference in a single time step of a timeseries can potentially propagate to all subsequent timestep, generating a high NRMSE without entailing significant operational differences. The VPP representation can be hence considered satisfying.

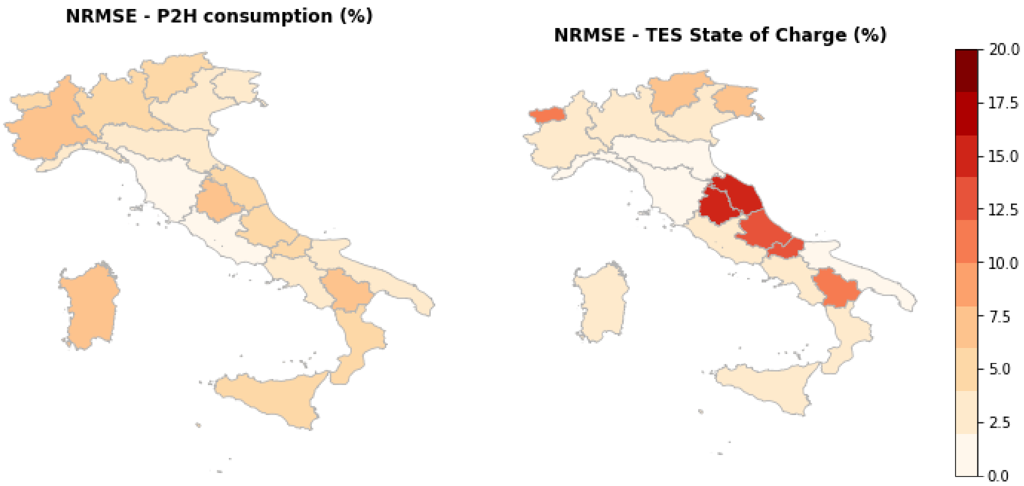

Fig. 8. Normalised Root Mean Square Error (NRMSE) between realistic aggregate and VPP representations of DLC P2H systems, for each Italian region.

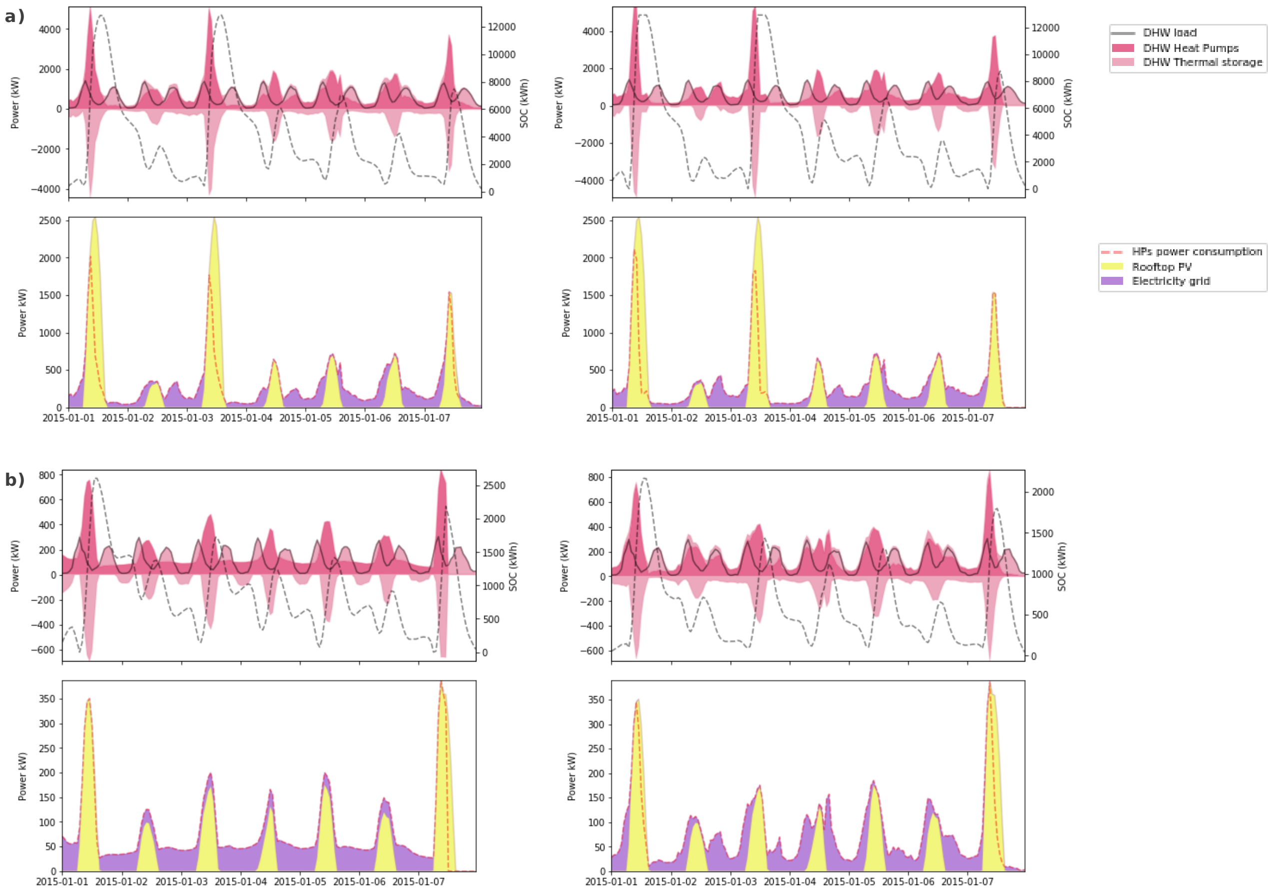

Fig. 9. Example of realistic (left) versus VPP-equivalent (right) aggregate operation of DLC P2H systems, for the regions Tuscany (a) and Marche (b) – the latter being the region with highest NRMSE.

3.4. Power-to-heat flexibility effects on the power system

As shown in Table 2, the impact of deep P2H penetration for standalone DHW consumption in Italy is positive, overall, for representative weeks in both winter and summer, and for all the studied configurations. In fact, the total power system ramping costs decrease in all cases, and more markedly for those configurations associated with a solar-friendly operation logic (PV-TC and DLC). In particular, the PV-TC configuration ensures the highest reduction of -8.2% in ramping costs for the winter-week case. Such strong reduction is explained by an increase in the electrical load precisely in the hours (the middle of the day) that are normally associated with a decrease in electricity demand in combination with an increase of PV output, and which hence typically provoke ramping of power plants. At the light of the net positive result for ramping costs, it can be concluded that the benefits of valley filling clearly outpace the possible steep-ramping effects mentioned in sub-section 3.2. A similar, although reduced, effect is registered for the DLC case. Most notably, the TPES of the integrated heat-electricity energy system experiences significant reductions. These increase with the smartness of the P2H configuration (from TC to DLC), reaching a maximum of -53.1 GWh/week for the DLC winter case and -89.5 GWh/week for the corresponding summer case. Such primary energy savings demonstrate the significant benefits of a deep penetration of P2H technologies, and hence the strong decarbonisation potential of heat-electricity integration.

Table 2. Summary of results of P2H impact on the energy system, for representative winter and summer weeks.

	Winter week			**Summer week**		
	TC	*PV-TC*	*DLC*	*TC*	*PV-TC*	*DLC*
Ramping costs [Δ%]	-2.7%	-8.2%	-3.3%	-1.9%	-3.9%	-4.3%

TPES [ΔGWh/week]	-11.6	-20.4	-53.1	-52.1	-59.1	-89.5

Larger decarbonisation effects might be achieved with increasing renewables penetration in the power system capacity mix. Figure 10 shows how P2H optimal operation is the result of a synergic effect between the PV generation profile and the hourly COP trend, both of which reach higher values during mid-day hours. The direct control of P2H aggregates allows to move the P2H load in moments in which renewables (and particularly PV) generation is higher, while also maximising at the same time the power-to-heat conversion efficiency. The expansion of PV capacity has hence the potential to maximise such synergic effect and ensure a deep DHW decarbonisation; in turns, P2H-DLC would ensure a mitigation of the possible PV curtailment in a highly-renewable system configuration.

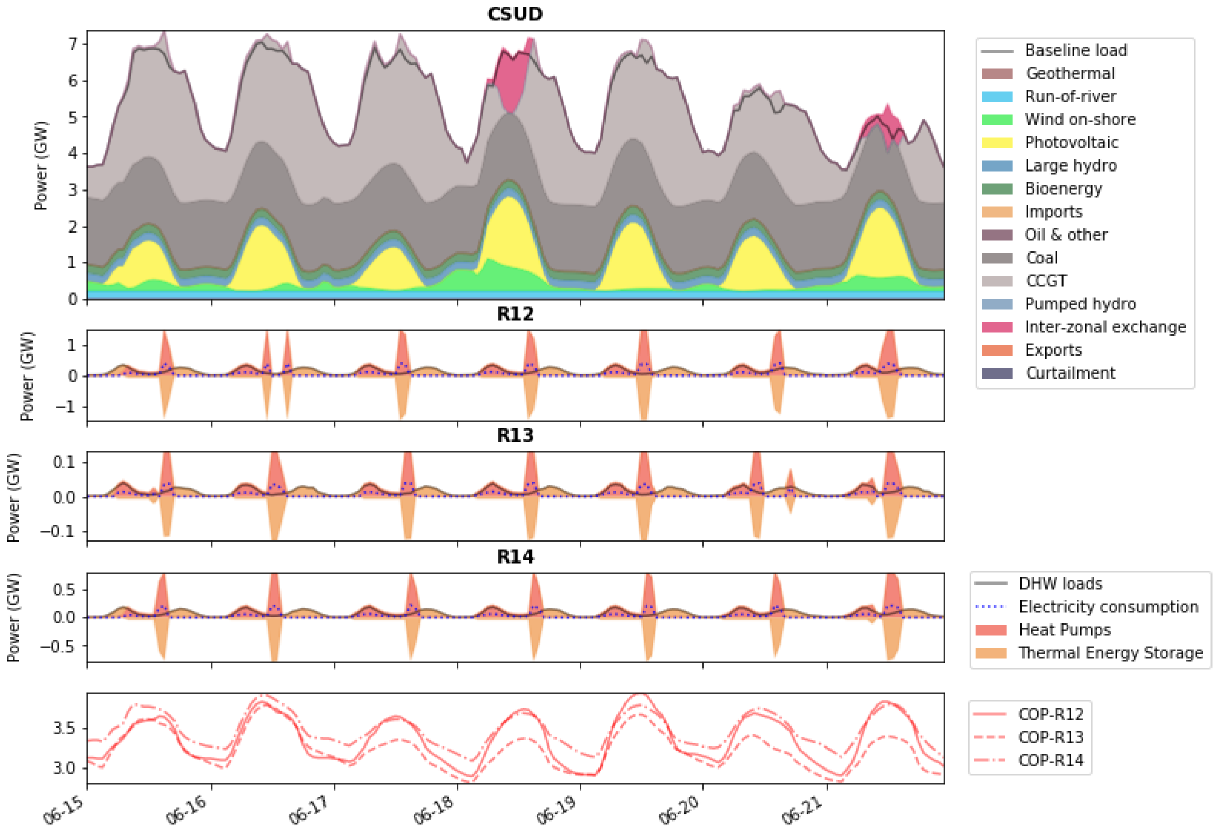

Figure 10. Power system hourly dispatch for the bidding zone CSUD and associated P2H-DLC operation of regional VPPs for the three regions (R12-Lazio, R13-Abruzzo, R14-Campania) comprising the CSUD zone, for a representative summer week. The bottom sub-plot shows the hourly COP trend in each region.

Conclusions

The deep penetration of P2H in energy systems has the potential to support decarbonisation and renewables integration, but requires ad-hoc modelling approaches to treat millions of dispersed loads within computationally-constrained ESOMs. This works shows, for the case of DHW provision, how large aggregates of both thermostatically-controlled and aggregator-controlled P2H systems can be modelled relying on bottom-up stochastic heat demand models coupled with simple thermodynamic representations. For the case of aggregator-controlled (DLC) P2H configurations, we also show that a VPP, with average characteristics of the set of interest, ensures satisfying accuracy in terms of aggregate consumption and TES state of charge, and can be applied within ESOMs for integrated heat-electricity optimisation. Finally, we demonstrate that all the considered P2H configurations provide net overall positive effects on the energy system in terms of power plant ramping costs reduction and, moreover, total primary energy supply reduction. A particularly promising and already applicable configuration is the so-called “smart-grid ready” (PV-TC), which automatically overcharges the TES when own or local PV production is detected. Still, the greatest decarbonisation potential can be achieved adopting a DLC smart configuration, which proves to be able to act as a low-cost flexibility and storage option for renewable production, facilitating further renewables capacity expansion. Nonetheless, it is worth noting that the latter configuration is here favoured by the perfect foresight assumed by the model. Further refinements of the analysis might focus on the application of a myopic optimisation approach.

Acknowledgments

The authors gratefully acknowledge the *Laboratoire de Thermodynamique* of the University of Liège for having hosted and supported Francesco Lombardi for 5 weeks during the conception of this work; Dr. Emeline Georges and Ioannis Boukas for having shared thoughts and previous expertise in the topic; and Eng. Christian Bernardoni for his advisory about commercial heat pump models and configurations.

Acronyms

DLC	direct load control
ESOM	energy system optimisation model
HP	heat pump
NRMSE	normalised root mean square error
P2H	power to heat
PV-TC	PV-coupled thermostatically-controlled loads
TC	thermostatically-controlled loads
TES	thermal storage
TPES	total primary energy supply
VPP	virtual power plant

References

[1] Eurostat, ‘Energy consumption in households - Statistics Explained’. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_consumption_in_households#Energy_consumption_in_households_by_type_of_end-use (accessed Dec. 06, 2019).

[2] K. Kavvadias, J. P. Jiménez-Navarro, G. Thomassen, European Commission, and Joint Research Centre, *Decarbonising the EU heating sector: integration of the power and heating sector*. 2019.

[3] K. Hedegaard and O. Balyk, ‘Energy system investment model incorporating heat pumps with thermal storage in buildings and buffer tanks’, *Energy*, vol. 63, pp. 356–365, 2013, doi: 10.1016/j.energy.2013.09.061.

[4] E. Georges, B. Cornélusse, D. Ernst, V. Lemort, and S. Mathieu, ‘Residential heat pump as flexible load for direct control service with parametrized duration and rebound effect’, *Applied Energy*, 2017, doi: 10.1016/j.apenergy.2016.11.012.

[5] N. Chapman, L. Zhang, N. Good, and P. Mancarella, ‘Exploring flexibility of aggregated residential electric heat pumps’, in *2016 IEEE International Energy Conference (ENERGYCON)*, Leuven, Belgium, Apr. 2016, pp. 1–6, doi: 10.1109/ENERGYCON.2016.7514082.

[6] D. Fischer, T. Wolf, J. Wapler, R. Hollinger, and H. Madani, ‘Model-based flexibility assessment of a residential heat pump pool’, *Energy*, vol. 118, pp. 853–864, Jan. 2017, doi: 10.1016/j.energy.2016.10.111.

[7] S. Eggimann, J. W. Hall, and N. Eyre, ‘A high-resolution spatio-temporal energy demand simulation to explore the potential of heating demand side management with large-scale heat

pump diffusion', *Applied Energy*, vol. 236, pp. 997–1010, Feb. 2019, doi: 10.1016/j.apenergy.2018.12.052.

[8] E. Georges, S. Quoilin, S. Mathieu, and V. Lemort, 'Aggregation of flexible domestic heat pumps for the provision of reserve in power systems.', *Proceedings of ECOS*, p. 12, 2017.

[9] D. Patteeuw, K. Bruninx, A. Arteconi, E. Delarue, W. D'haeseleer, and L. Helsen, 'Integrated modeling of active demand response with electric heating systems coupled to thermal energy storage systems', *Applied Energy*, vol. 151, pp. 306–319, Aug. 2015, doi: 10.1016/j.apenergy.2015.04.014.

[10] S. Pfenninger and B. Pickering, 'Calliope: a multi-scale energy systems modelling framework', *Journal of Open Source Software*, Sep. 12, 2018. https://joss.theoj.org (accessed Nov. 01, 2019).

[11] ISTAT, 'I consumi energetici delle famiglie'. 2013, Accessed: Dec. 27, 2019. [Online]. Available: https://www.istat.it/it/files//2014/12/StatReport_Consumi_energetici.pdf.

[12] F. Lombardi, S. Balderrama, S. Quoilin, and E. Colombo, 'Generating high-resolution multi-energy load profiles for remote areas with an open-source stochastic model', *Energy*, vol. 177, pp. 433–444, Jun. 2019, doi: 10.1016/j.energy.2019.04.097.

[13] F. Lombardi, B. Pickering, S. Pfenninger, and E. Colombo, 'Policy decision support for renewables deployment through spatially explicit practically optimal alternatives', *[under review, Joule]*.

[14] F. L. Müller and B. Jansen, 'Large-scale demonstration of precise demand response provided by residential heat pumps', *Applied Energy*, vol. 239, pp. 836–845, Apr. 2019, doi: 10.1016/j.apenergy.2019.01.202.

[15] European Commission, 'The future electricity intraday market design', doi: 10.2833/004191.

[16] D. Fischer, T. Wolf, J. Scherer, and B. Wille-Haussmann, 'A stochastic bottom-up model for space heating and domestic hot water load profiles for German households', *Energy and Buildings*, vol. 124, pp. 120–128, Jul. 2016, doi: 10.1016/j.enbuild.2016.04.069.

[17] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegård, and E. Wäckelgård, 'Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation', *Energy and Buildings*, vol. 41, no. 7, pp. 753–768, Jul. 2009, doi: 10.1016/j.enbuild.2009.02.013.

[18] F. Lombardi, M. V. Rocco, and E. Colombo, 'A multi-layer energy modelling methodology to assess the impact of heat-electricity integration strategies: The case of the residential cooking sector in Italy', *Energy*, vol. 170, pp. 1249–1260, Mar. 2019, doi: 10.1016/j.energy.2019.01.004.

[19] E. McKenna and M. Thomson, 'High-resolution stochastic integrated thermal–electrical domestic demand model', *Applied Energy*, vol. 165, pp. 445–461, Mar. 2016, doi: 10.1016/j.apenergy.2015.12.089.

[20] F. Lombardi, *Repository: Modelling distributed Power-to-Heat technologies as a flexible virtual power plant for smart heat-electricity integration*. Zenodo, 2020.

[21] O. Dumont, C. Carmo, R. Dickes, E. Georges, S. Quoilin, and V. Lemort, 'Hot water tanks : How to select the optimal modelling approach?', *CLIMA conference*, p. 10, 2013.

[22] I. Staffell, D. Brett, N. Brandon, and A. Hawkes, 'A review of domestic heat pumps', *Energy Environ. Sci.*, vol. 5, no. 11, p. 9291, 2012, doi: 10.1039/c2ee22653g.

[23] Terna (Italian TSO), 'Terna Transparency report', doi: https://www.terna.it/en/electric-system/transparency-report.

[24] Open Power System Data, 'Time series', doi: https://doi.org/10.25832/time_series/2019-06-05.

[25] V. Corrado, I. Ballarini, and S. P. Corgnati, *Building Typology Brochure - Italy*. 2014.

[26] E. Fuentes, L. Arce, and J. Salom, 'A review of domestic hot water consumption profiles for application in systems and buildings energy performance analysis', *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 1530–1547, Jan. 2018, doi: 10.1016/j.rser.2017.05.229.