Electrical Flexibility Forecasting and Assessment for Heat-Pump-Based District Heating Systems

Roberto Rocca[1], Lorena Elorza-Uriarte[2], Arjen Schamhart[3], Gerwin Verschuur[4], and David Miguel Rivas-Ascaso[2]

[1]https://orcid.org, CIRCE Mixed Research Institute (University of Zaragoza, CIRCE Technology Centre) Zaragoza
[2]Electrical Systems Department CIRCE Technology Centre Zaragoza, https://orcid.org
[3]Energie Samen Rivierenland Culemborg
[4]Thermo Bello BV

July 18, 2024

Abstract

Nowadays, simple and cost-effective solutions to extract flexibility from any possible energy asset are being heavily investigated, along with optimal strategies to offer flexibility in different markets. In this context, this work proposes an Electrical Flexibility Forecasting Engine (EFFE) conceived for district heating systems based on centralised heat pumps. The idea is implemented in the case study of Culemborg (ND), demo site of the H2020-ACCEPT project. Here, the engine is run in a typical winter day to forecast and asses both upwards and downwards flexibility, along with the minimum economically viable bids for a local market.

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Roberto Rocca
CIRCE Mixed Research Institute (University of Zaragoza and CIRCE Technology Centre)
Zaragoza, Spain
https://orcid.org/0000-0001-5996-2755

Lorena Elorza-Uriarte
Electrical Systems Department
CIRCE Technology Centre
Zaragoza, Spain
https://orcid.org/0000-0002-9698-8337

Arjen Schamhart
Energie Samen Rivierenland
Culemborg, the Nederlands
arjen.schamhart@energiesamenrivierenland.nl

Gerwin Verschuur
Thermo Bello BV
Culemborg, the Nederlands
gerwin@thermobello.nl

David Miguel Rivas-Ascaso
Electrical Systems Department
CIRCE Technology Centre
Zaragoza, Spain
https://orcid.org/0000-0003-0060-5344

***Abstract*—Nowadays, simple yet cost-effective solutions to extract flexibility from all possible energy devices are heavily investigated, together with optimal strategies to offer flexibility either in demand response programs or local flexibility markets (LFMs). In this context, this work proposes an Electrical Flexibility Forecasting Engine (EFFE) for district heating systems using centralised heat pumps. Starting from weather forecasts and electricity price signals, EFFE firstly forecasts the thermal power demand through an artificial neural network, and subsequently forecasts the electrical flexibility available over the desired time horizon. The idea is implemented in the case study of Culemborg (ND), demo site of the H2020-ACCEPT project, where EFFE is run in a typical winter day to forecast and asses both upwards and downwards flexibility, as well as the minimum economically viable bids to participate in a LFM.**

***Index Terms*—District heating, local flexibility market, flexibility, forecasting, heat pump, market bidding, sector coupling**

I. Introduction

The rapid increase in renewable energy penetration in distribution grids is requiring the development of simple yet cost-effective solutions to prevent and avoid any risks of localised overvoltage and/or congestion. As part of the solution, installation of Energy Storage Systems (ESSs), either centralised or distributed, is considered the most straightforward solution [1], [2]. However, Demand-Side Management (DSM) schemes also represent a further alternative siding ESSs. In this case, the idea is to reshape the energy demand curve by offering consumers either time-dependent energy tariffs and/or direct monetary incentives with the objective of "inviting" them to change their habitual consumption patterns, and thus help solving or preventing overvoltage and/or congestions [3]. The possibility for customers to participate in DSM introduces the concept of *flexibility*, that is, *the ability of increasing or decreasing a customer electric demand at will in response to an external signal* [4]. In particular, there exist two main sources of the bespoke signal. The first is a direct emission from the Distribution System Operator (DSO); the second is the result of a trade in a Local Flexibility Market (LFM), where the DSO participates as buyer and customers as sellers [5].

In this scenario, more and more solutions are being proposed to extract flexibility from all energy assets. As an example, electric vehicles emerge as potentially the most flexible class of loads [6], [7], as charging/discharging patterns can be easily shifted in time and modulated in intensity. Besides, Sector Coupling (SC) may also provide an impactful source of flexibility [8]. Further into details, SC can be implemented through both centralised district-level assets, as well as distributed user-level assets. This work focuses on SC between electricity and heat vectors through only centralised assets. In this case, flexibility can be obtained from either Combined Heat and Power Systems (CHPSs) [9], or District Heating Systems (DHSs) based on HPs [10]; although possibility to extract flexibility from traditional DHSs is being also investigated [11].

With regards of HP-Based DHSs, research currently covers several aspects: preheating DH water through HPs to improve energy efficiency [12], model predictive controls to coordinate distributed HPs with centralised HPs or CHPSs [13], or eventually co-optimisation for coupled thermal and electrical networks for both dispatch [14] and planning [10] purposes. Regarding the markets, offering flexibility in reserve capacity and ancillary services are currently the most explored options [10], [13].

The above analysis points out that neither the flexibility forecasting problem of HP-Based DHSs has been addressed so far, nor their participation in LFMs. In order to fill these gaps found in the current state of the art, this work wishes to provide a twofold contribution:

1) Propose a novel Electrical Flexibility Forecasting Engine (EFFE), conceived for HP-Based DHSs.
2) Evaluation and assessment of the flexibility of a HP-Based DHS available in a typical winter day, along with an estimation of the minimum economically viable bids for a LFM.

This work has been developed within the framework of the H2020 - ACCEPT project, which has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 957781.

The idea is implemented in the case study of Culemborg (ND), demo site of the H2020-ACCEPT project [15].

II. Heat-Pump-Based District Heating Systems, Flexibility and Flexibility Markets

A. Flexibility Definition and Local Flexibility Markets

As mentioned in the Introduction, *flexibility* ϕ is referred to as the the ability of increasing or decreasing a customer electric demand at will in response to an external signal. In particular, when demand is increased $P_{el}|_{up}$ flexibility is referred to as *downwards*, ϕ_{do}; when demand is decreased $P_{el}|_{do}$ flexibility is named *upwards*, ϕ_{up}. Both ϕ_{do} and ϕ_{up} have to be evaluated against a baseline demand $P_{el}|_{base}$:

$$\phi_{do/up}(t) = P_{el}(t)|_{up/do} - P_{el}(t)|_{base}\,. \tag{1}$$

As also discussed in the Introduction, flexibility signal can be the result of a trade in a LFM. In this case, an auction process is opened in a market platform where all customers belonging to the distribution grid zone requiring flexibility, the Minimum Market Bid (MMB) needs to be evaluated to ensure economic viability from the market participation. In particular, the MMB is defined as the variation in electricity cost Δc_{el} caused by the change from the baseline to the new operation:

$$MMB = \Delta c_{el}. \tag{2}$$

The way a flexibility event is undergone and hence Δc_{el} and MMB calculated depend on the DH system at hand. In this work, this aspect is addressed directly for the Culemborg case study in Section V.

The final point to note is that auctions in the LFM take place from hours to months ahead the moment of delivery. Therefore, accurate forecasting of $\phi_{up/do}$ with the corresponding $MMBs$ is necessary prior to trading in a LFM. To this end, an EFFE is proposed in this work, which is described in Section III.

B. HP-Based DH Systems: Architecture, Control and Flexible Control

In a HP-Based DHS, the heat-carrying fluid is usually hot water in the range of 50ºC/60ºC, which is generated in one or more thermal plants and then delivered to several end users through a piping network. A simplified example is shown in Fig. 1, where its main components are illustrated:

1) One or more centralised thermal units, counting with one or more HPs, sometimes sided by combustion-based heaters, boosters or backup boilers, and a storage tank.
2) A pressurised piping system transporting hot water, which is commonly referred to as 'primary' circuit.
3) A heat delivery substation per customer.
4) Customers internal 'secondary' hot-water distribution systems.

At a centralised level, two main controls regulate the system. The first acts on the thermal unit, whereas the second on hot-water distribution. With regards of the former, the main control variable is the tank hot-water temperature T_{tank}. As illustrated in Fig. 2, T_{tank} is controlled by the HP via a PI or any other type of controller that follows a reference value $T_{tank-ref}$.

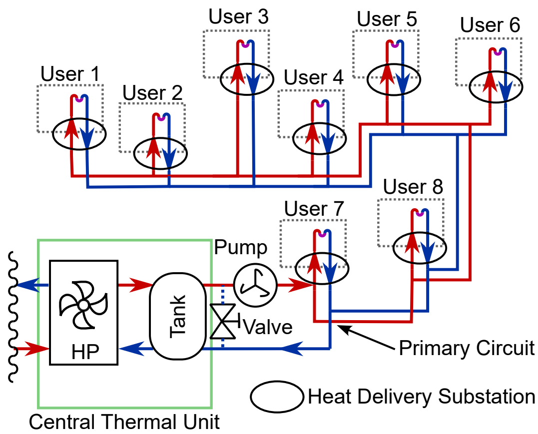

Fig. 1. Example of District Heating Systems.

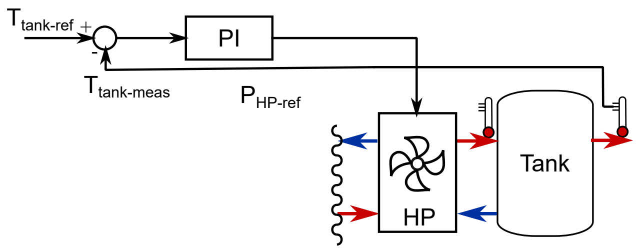

Fig. 2. Centralised Heat Pump Control.

Based on the above, $\phi_{up/do}$ may be obtained by lowering or rising $T_{tank-ref}$ within a permitted range. In this way, the HP controller is forced to either increase (ϕ_{do}) or decrease (ϕ_{up}) the output power.

Furthermore, at any time instant, flexibility time Δt_{ϕ} needs to be defined as well. This last defines the period of time during which the power variation with respect to the baseline can be maintained and is equal to the time that T_{tank} would take to reach the new $T_{tank-ref}$ emitted in response to a flexibility signal. In this way, for any time instant, a pair of T_{tank} vs. t curves is obtained, as shown in Fig. 3, where dashed lines represent the heating or cooling process in case flexibility is activated.

III. Electrical Flexibility Forecasting Engine

Following from subsection II-A, the EFFE is now presented. The architecture is shown in Fig. 4. By starting from the left, a weather Application Programming Interface (API) provides the required weather data. Heat demand data are also constantly retrieved from the HP meter. Eventually, should a real-time pricing being used, electricity prices are also retrieved.

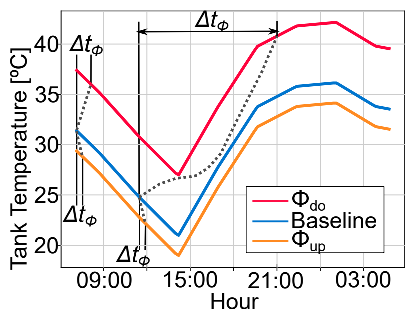

Fig. 3. Examples of flexibility times vs. time curves.

Subsequently, data are stored in a Data Space (DS), which, in turn, feeds an Artificial Neural Network (ANN) that forecasts the heat consumption $Q_{dem-fore}$ and is described in subsection III-A. Finally, $Q_{dem-fore}$ is fed into the physical model of the HB-based DHS that generates the flexibility and flexibility times forecasts, as shown in subsection III-B (as explained later, the forecasted ambient temperatures $T_{amb-fore}$ represents a further input).

Granularity of data and time horizon of future forecasts used in this work are reported in Table I. The whole routine runs in Python and is refreshed every 30 minutes.

TABLE I
FLEXIBILITY FORECASTING ENGINE PARAMETERS

Parameter	Unit	Value
Granularity	mins	30
Time Horizon	hours	24
Refreshment frequency	mins	30

A. ANN-Based Heat Demand Forecasting

The list of variables composing the ANN input layer is provided in Table II. As it can be seen, variables are divided into five blocks.

The first block contains variables obtained by processing dates and times. In particular, a 1D-to-2D transformation is applied in order to take periodic properties of hours, days and months into account as explained in [16].

The second block contains two dummy variables, which assume a 0 or 1 value. The first represents a working or non-working day. The second represents whether the day at hand falls into the heating season or not, that is, the season during which customers are allowed to turn the heating on.

The third block is composed of whether variables, whereas the fourth by variables obtained from historical values of the ambient temperature T_{amb}.

B. HP-Based DH System Modelling

As mentioned above, this work considers the DH system of Culemborg (ND), demo sites of the H2020 ACCEPT project [15], as case study. The Culemborg DHS has been modelled in Open Modelica [17], as shown in Fig. 5. In particular, the model has been developed based on the following simplifying hypotheses, which have been introduced in order to obtain a reasonable compromise between accuracy and complexity, while keeping computation time below the refreshment rate, i.e., 30 minutes:

- All users are replaced by an equivalent aggregated user.
- Thermal inertia of metal parts is neglected.
- HP and tank are connected to the equivalent customer without mixing valve.
- Thermal losses are neglected.

TABLE II
HEAT DEMAND FORECASTING ANN INPUT VARIABLES

Group	Variable	Description
Datetime	$Hourmin$	Normalised minute value
	$Hour_x$	Hour x-component
	$Hour_y$	Hour y-component
	Day_x	Day x-component
	Day_y	Day y-component
	$Month_x$	Month x-component
	$Month_y$	Month y-component
Calendar	$Holiday$	Working day or not
	$Winter$	Winter season
Weather	T_{amb}	Outside Temperature [ºC]
	T_{dew}	Dew Point Temperature [ºC]
	w_s	Wind Speed [m/s]
	C_c	Clouds Coverage [%]
	H_r	Relative Humidity [%]
Temperature	$T_{amb[i-1]}$	T_{amb} at previous time step [ºC]
	T_{AVG6}	Average T_{amb} last 6 hours [ºC]
	T_{AVG12}	Average T_{amb} last 12 hours [ºC]
	T_{AVG24}	Average T_{amb} last 24 hours [ºC]
Heat Demand	$Q_{dem[i-1]}$	Q_{dem} at previous time step $[\mathrm{kW_{th}}]$
	Q_{AVG6}	Average Q_{dem} last 6 hours $[\mathrm{kW_{th}}]$
	Q_{AVG12}	Average Q_{dem} last 12 hours $[\mathrm{kW_{th}}]$
	Q_{AVG24}	Average Q_{dem} last 24 hours $[\mathrm{kW_{th}}]$

- Thermal stratification in the tank is neglected.

As it is the case for the Culemborg DHS, $T_{tank-ref}$ is generated from the forecasted outer temperature $T_{amb-fore}$, while the HP maximum power $P_{HP}(t)|_{max}$ is imposed by the produced hot-water temperature and the HP minimum power $P_{HP}(t)|_{min}$ is set at 10% of $P_{HP}(t)|_{max}$. Eventually, the model forecasts for the following flexibility-related variables:

- $P_{HP}(t)|_{max}$, $P_{HP}(t)|_{min}$ and $P_{HP}(t)|_{base}$.
- ϕ_{do} and ϕ_{up}.
- $\Delta t_{\phi-do}$ and $\Delta t_{\phi-up}$.
- MMB_{do} and MMB_{up}.

IV. THE CULEMBORG CASE STUDY

The Culemborg case study considered in this work is based on a typical winter day, which is characterised by the outside temperature profile of Fig. 6, along with the hourly electricity prices of Fig. 7 [18].

The Culemborg DH system relies on a HP of 1235 $\mathrm{kW_{th}}$, producing hot water between 35ºC and 50ºC with a COP varying between 4.5 and 7. In terms of flexibility, the DHS operator permits temporary operation with ΔT_{tank} of -2ºC and +6ºC with respect to the baseline condition. Here, it is important to observe that the flexibilised operation discussed in this work has been developed based on a non-intrusiveness principle. In simple words, flexibility needs to be obtained with no major changes in the existing hardware and control systems. Based on that, flexibility is treated as an additional

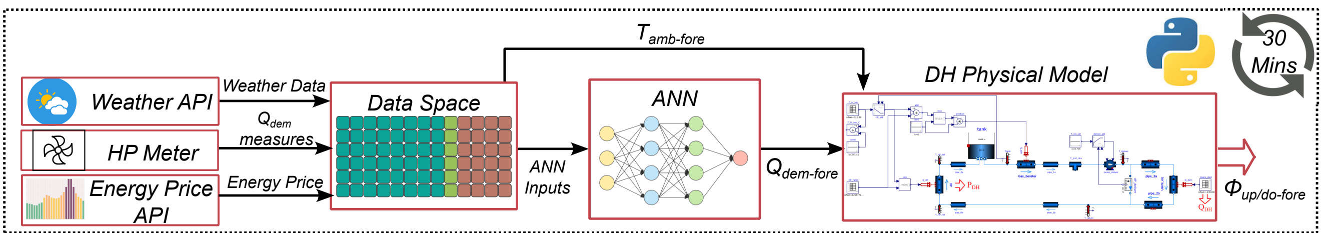

Fig. 4. Electricity Flexibility Forecasting Engine.

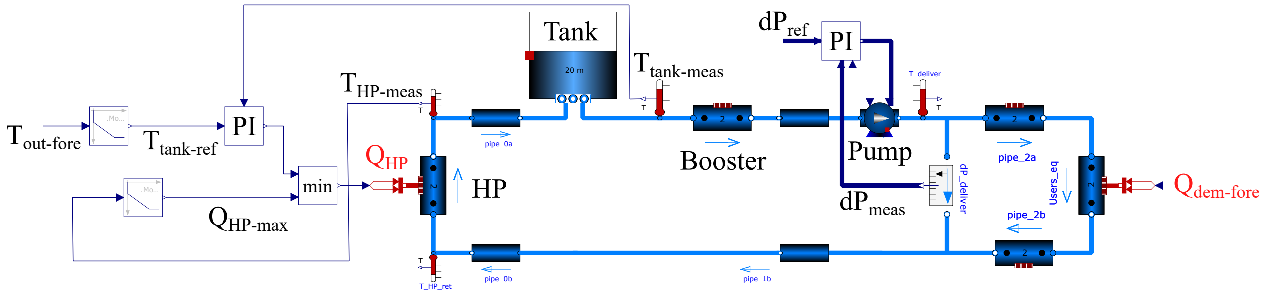

Fig. 5. Culemborg HP-Based DHS Model in Open Modelica.

signal that temporarily supersedes the PI controller, until the maximum or minimum permitted temperature is reached:

- $P_{HP}(t)|_{min}$ for ϕ_{up},
- $P_{HP}(t)|_{max}$ for ϕ_{do}.

V. Results and Discussion

Following from the previous sections, EFFE is run for the bespoke typical winter day. Forecasted vs. measured/simulated results are shown in Fig. 8(a)-(d), respectively in orange and blue lines. In particular, Fig. 8(a) shows the thermal demand obtained through the ANN, which has been trained with two years of historical data. Fig. 8(b) and (c) illustrate the electric power and its corresponding flexibility, which has been obtained in accordance with (1). Eventually, Fig. 8(d) quantifies the flexibility times in accordance with what explained for Fig. 3.

Forecast accuracy is assessed in Table III. Overall, relatively accurate predictions can be observed for Q_{dem}, P_{el}, $\Delta t_{\phi-do}$ and $\Delta t_{\phi-up}$, with discrepancies in the range of $\pm 30\%$. Here, the small difference in error between Q_{dem} and P_{el} is caused by the different CoPs corresponding to the actual and forecasted Q_{dem}. Conversely, considerable discrepancies in the range of -50% to +100% are obtained for ϕ_{do} and ϕ_{up}, highlighting a significant error amplification effect as one moves from power to flexibility, and thus the necessity of extremely accurate forecasting models. As one

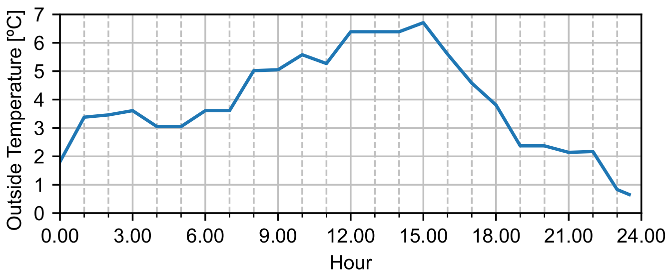

Fig. 6. Outside Temperature of Typical Winter Day.

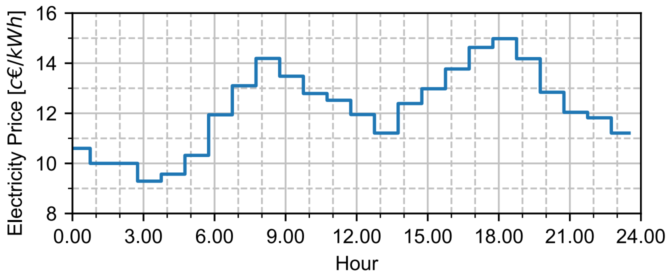

Fig. 7. Hourly Electricity Price of Typical Winter Day.

may see, peak errors are incurred with the HP operating at peak load (11 A.M.). Thus, a possible source of error is the scarcity of historical data nearby peak load conditions available for training the ANN.

TABLE III
Flexibility Forecasting Accuracy Assessment

Variable	MAPE	Max. Err. [%]	Min. Err. [%]
Q_{dem}	8.9	24.09	-33.59
P_{HP}	9.37	30.71	-36.65
ϕ_{do}	9.9	106.57	-29.17
ϕ_{up}	11.88	38.66	-48.96
$\Delta t_{\phi-do}$	7.25	15.27	-17.07
$\Delta t_{\phi-up}$	8.0	23.03	-25.71

Concerning the $MMBs$, its evaluation requires the definition of the HP-based DHS behaviour. Here, a first simplifying hypothesis is made that the DHS responds instantaneously to the the new power signal. An example of downwards flexibility event is shown in Fig. 9, where maximum HP power is activated at time t_a for its corresponding $\Delta t_{\phi-do}$. Then, a second simplifying hypothesis is made that baseline operation is restored as soon as the flexibility event terminates (t_f). This assumption is introduced in line with the non-intrusiveness principle mentioned above, as well as in order not to depend on an optimisation process and thus maintain the example complexity at a reasonable level. At this point, the same amount of energy stored in the tank during the flexibility event (E_{flex} in Fig. 9) is returned by operating the HP at $P_{HP}(t)|_{min}$ until t_f. Therefore, MMB_{do} is equal to the difference in electricity cost between flexibility and normal operation Δc_{el-do} and $\Delta c_{el-base}$:

$$MMB_{do} = \Delta c_{el-do} - \Delta c_{el-base} = \int_{t_a}^{t_r} \pi_{el}(t)\; P_{HP}(t)|_{max}\, dt + \int_{t_r}^{t_f} \pi_{el}(t)\; P_{HP}(t)|_{min}\, dt - \int_{t_a}^{t_f} \pi_{el}(t)\; P_{HP}(t)|_{base}\, dt \quad (3)$$

MMB_{up} may be evaluated in an analogous manner by inverting operation at minimum and maximum power:

$$MMB_{up} = \Delta c_{el-up} - \Delta c_{el-base} = \int_{t_a}^{t_r} \pi_{el}(t)\; P_{HP}(t)|_{min}\, dt + \int_{t_r}^{t_f} \pi_{el}(t)\; P_{HP}(t)|_{max}\, dt - \int_{t_a}^{t_f} \pi_{el}(t)\; P_{HP}(t)|_{base}\, dt \quad (4)$$

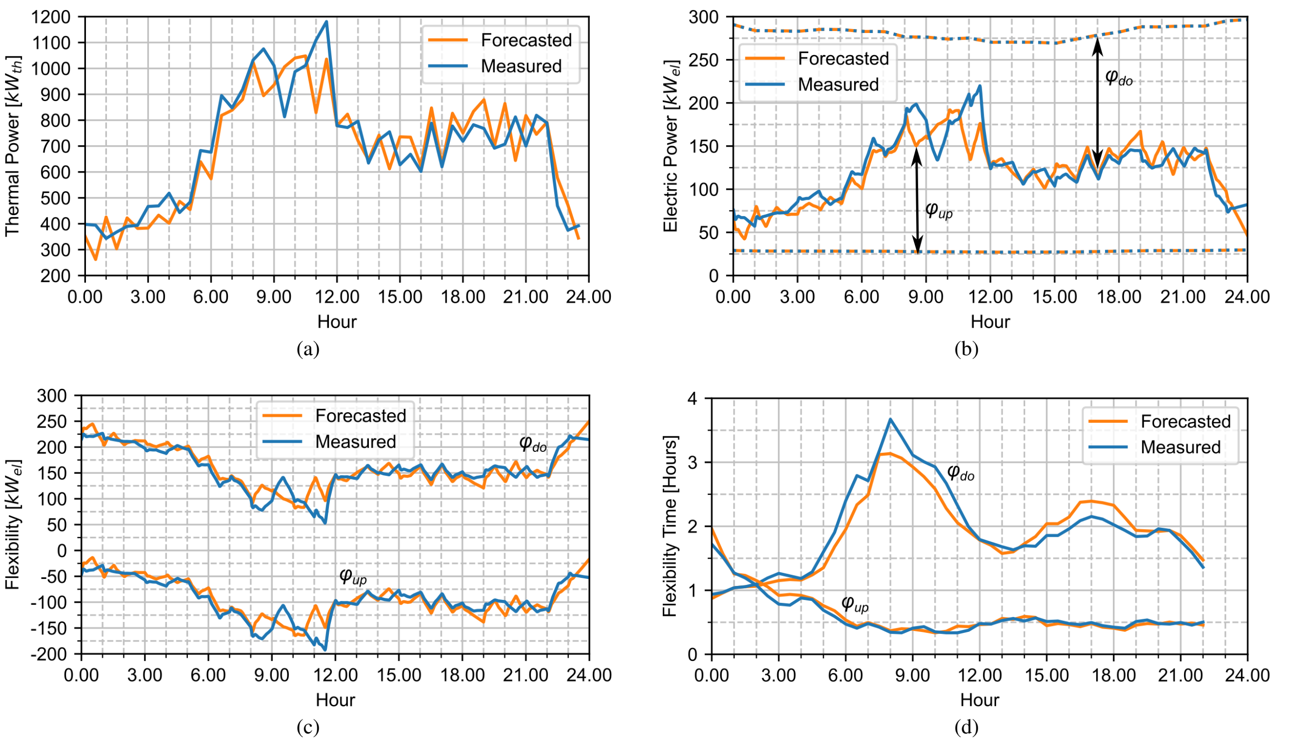

Fig. 8. Typical Winter Day Forecasting Results: (a) Heat demand, (b) Electric Power, (c) Downwards and Upwards Flexibility, (d) Downwards and Upwards Flexibility Time.

For the case study at hand, MMB_{do} and MMB_{up} are plotted in Fig. 10. As it can be seen, MMB_{do} oscillates between -8€ and 7€, whereas MMB_{up} stands in the range of -1€ and 0.5€. This difference stems from the higher values of ϕ_{do} and $\Delta t_{\phi-do}$, which, in turn, stem from the higher upwards temperature variation allowed. The second point to note is concerned with the negative values of MMB_{do} and MMB_{up}, which are due to the fact that HP operation does not take electricity price into account. $MMBs$ forecast accuracy is assessed in Table IV, where non negligible maximum and minimum errors are attained, indicating that more work is needed to further improve the forecasting models.

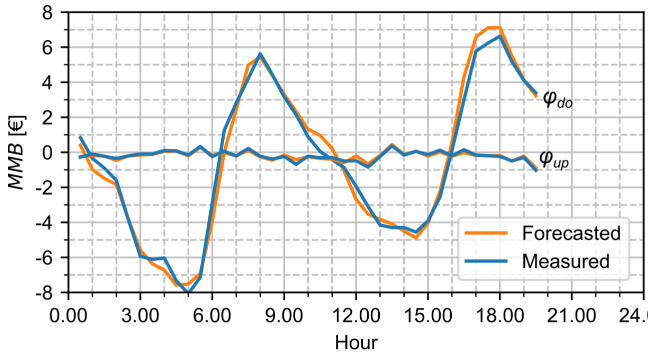

Fig. 10. Typical Winter Day Forecasting Results: $MMBs$.

TABLE IV
$MMBs$ Forecasting Accuracy Assessment

Variable	MAPE	Max. Err. [%]	Min. Err. [%]
MMB_{do}	10.53	43.82	-13.73
MMB_{up}	22.37	32.38	-57.23

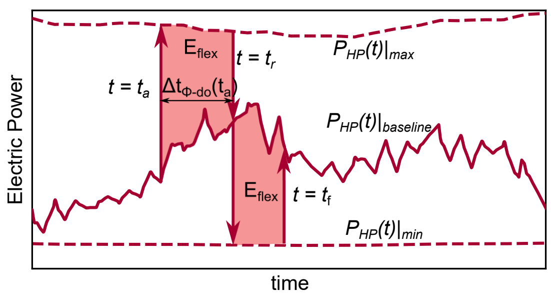

Fig. 9. Example of Downwards Flexibility Activation.

VI. Conclusion

In this work, a novel Electrical Flexibility Forecasting Engine (EFFE) for HP-based DH system has been proposed and run for a typical winter day in the Culemborg case study. Then, the main flexibility-related quantities have been forecasted and their values assessed.

In terms of flexibility, the HP has proved to be an invaluable source, featuring up to 200kW$_{el}$ upwards and 250kW$_{el}$ downwards, with times of up to 2 hours upwards and 3.5 hours downwards. In terms of forecast accuracy, despite a very good average accuracy obtained for all quantities, peak errors in the range of -50% to +100% have been obtained in flexibility forecasting, highlighting so the need to further improve the modelling accuracy. On the other hand, accurate predictions have been attained for $\Delta t_{\phi-do}$ and $\Delta t_{\phi-up}$, with discrepancies in the range of $\pm 30\%$.

Concerning the $MMBs$, values found are in the range of -1€ and 0.5€ for upwards flexibility, and -8€ and 7€ for downwards flexibility, although forecast error analysis highlighted the necessity to increase accuracy further.

Overall, this work provided an excellent starting point for flexibility forecasting and assessment of HP-based DH systems. Future work will revolve around the improvement of the demand forecasting methodology, more accurate system-level modelling through the removal of the simplifying hypothesis made in subsection III-B, starting from the thermal losses, as well as an optimised strategy to restore normal operation after flexibility activation.

Acknowledgment

Authors wish to express their gratitude to Energie Samen Rivierenland (ESR) and Thermo Bello BV for their technical support and the provision of real aggregated consumption data.

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