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ORIGINAL RESEARCH

Demand flexibility modelling for long term optimal distribution grid planning

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Abstract

Optimisation tools for long-term grid planning considering flexibility resources require aggregated flexibility models that are not too computationally demanding or complex. Still, they should capture the operational benefits of flexibility sufficiently accurately for planning purposes. This article investigates the sufficiency of an aggregated flexibility model for planning tools by comparing it against a detailed flexibility model. Two different constraint formulations, namely based on recovery period and temporal proximity, were tested to account for post activation dynamics of flexibility resources. The results show that the recovery period based formulation results in excessive demand reduction. The proximity constraint formulation on the other hand results in realistic activation of flexibility resources, which represents an improvement over the base formulation without constraints for post activation dynamics. The results show how a too simple model of the operational behaviour of demand flexibility may overestimate its benefits as an alternative or supplement to grid investments.

1 | INTRODUCTION

Distribution grids have traditionally been designed to handle the load flows of the peak load hour, and local congestions and voltage quality problems are solved by grid reinforcements. There is an increased interest in utilising flexibility resources as an alternative or supplement to the traditional grid infrastructure in the grid planning process. Flexibility resources include, for example, industrial and residential shiftable loads and energy storage systems which may be activated for peak shaving or voltage control and thereby reduce needs of investment in traditional grid infrastructure [1].

Traditional infrastructure such as power lines and cables, transformers, and compensators have well-determined capacities. The potential and capacity of flexibility resources, on the other hand, are highly dependent on operational conditions. The benefits of flexibility in terms of reduced or deferred grid investment costs are thus determined by their behaviour during grid operation. In order to take flexibility resources into account in long-term distribution grid planning, models capturing the relevant operational constraints and benefits are needed in the software tools used for grid planning. The requirements for such flexibility models depend on two major factors: The first is the types of grid services being considered in the planning tool; the second is the level of aggregation or simplification to be taken, driven by computational limitations and data availability. A general requirement is that it is important to capture constraints related to temporal interdependencies in the flexibility resources. This is a new requirement that did not apply to planning tools in which only traditional grid infrastructure is considered.

Existing demand flexibility models in the literature are either developed and applied from an operational perspective or from a long-term planning perspective. For the first type of models, the focus is typically on the modelling of activation, rebound effects and aggregation of individual flexibility resources (e.g. individual loads within households) [2]. Optimisation models for long-term grid planning purposes, on the other hand, typically only allow for a simplified mathematical representation of grid operation and flexibility activation. Computational complexity is one important reason, since such models also need to consider power flow constraints in an extended grid area and over an extended time horizon with multiple investment options [3–8].

A number of works have analysed the temporal modelling of demand flexibility models with the aim of computational efficiency. Avramidis et al. propose a linear approximation to deal with the binary nature of shiftable loads in multi-period optimal power flow and compare it to a non-linear formulation [9]. A linear programming approach is used in [10] to provide optimal residential load control in real-time pricing environments. Simplified power-time flexibility models are introduced in [11] to investigate the potential of load shifting on large scale. In [12], two types of flexible demand models, namely directly and storage managed flexible demand models, are introduced in the context of active distribution management. Vanin et al. focus on the modelling of binary constraints and apply different linearisations and convex relaxations to model flexibility in unbalanced three phase networks [13].

As for long-term grid planning applications, Klyapovskiy et al. propose a framework for incorporating flexibility and use a simulation based approach to compare investment options in a medium voltage distribution grid [14]. Utilisation of demand response to balance for wind power generation uncertainty is analysed in [15] utilising a simplified demand response model based on assumed demand response bids. Noucier et al. analyze the effects of implicit and explicit incentives on distribution system investments utilising a bi-level optimisation model [16], whereas [17] uses a two-stage optimisation model for optimal investment sizing, utilising Benders decomposition. Grid expansion models including implicit (price-dependent) demand response programs and investments to enable load shifting are proposed in [18] and [19], respectively.

Although a variety of demand flexibility models exist for long-term planning and for operational studies, the methodologies presented in the literature are often limited to load reduction (curtailment) [15, 16] or rely on given ranges for up and downward flexibility provision [12, 14, 17–19] and load recovery times [14, 19] for tractable formulation of the optimisation problem. However, the effects of generalisation and parametrisation of such models on the accuracy have not been discussed sufficiently in the literature, which is the aim of this article.

Although a variety of demand flexibility models exist for long-term planning and for operational studies, the methodologies presented in the literature often rely on given ranges for up and downward flexibility provision and load recovery times for tractable formulation of the optimisation problem. However, the effects of generalisation and parametrisation of such models on the accuracy have not been discussed sufficiently in the literature, which is the aim of this article.

Here, we combine the long-term planning perspective and the operational perspective by applying a generic, parametrised demand flexibility model designed for long-term planning and comparing it to a more detailed, operational model. Our focus is on residential demand flexibility resources and on capturing flexibility services for congestion management in distribution grids. Our motivation is the need for a demand flexibility model that represents the operational behaviour of demand flexibility sufficiently accurately for the purpose of distribution grid planning studies while still being relatively generic and not demanding in terms of input data requirements. In simple terms, the general research question is: How does the operational benefits and costs of demand flexibility, as an alternative or supplement to grid investments, depend on how demand flexibility is modelled?

In particular, we will assess the sufficiency of possible mathematical formulations for representing rebound effects in long-term grid planning tools. If such temporal interdependencies are not properly accounted for, planning tools may overestimate the operational benefits when comparing the use of flexibility to investment in traditional grid infrastructure.

With respect to the literature summarised above, this article presents the following main contributions:

- It presents a generic model of demand flexibility, including two novel formulations for temporal interdependencies. This demand flexibility model is incorporated in a comprehensive tool for optimal long-term grid planning considering power flow and grid constraints.
- It provides the parameterisation of the generic flexibility model based on real load demand data and more detailed models of selected individual demand flexibility resources.
- By comparing the generic and the detailed flexibility model, the sufficiency of the generic demand flexibility model for grid planning is investigated. This investigation identifies and illustrates effects that are not captured by the more coarse-grained generic flexibility model but that are relevant for long-term grid planning purposes (e.g. rebound effects).

The rest of the article is structured as follows. First, models for demand flexibility are introduced in Section 2, including (a) detailed models of individual flexibility resources and (b) a generic demand flexibility model for aggregated flexibility resources. The flexibility representations are investigated and compared using a test case in Section 3. The findings are summarised in Section 4.

2 | MODELLING OF FLEXIBILITY RESOURCES

This section first describes the models for selected individual demand flexibility resources in the residential sector that we consider as examples in this article (Section 2.1). It then describes how they are activated according to a *detailed operational model* for demand flexibility in Section 2.2. Since these models need to capture the time dependencies and rebound characteristics for the load types and geographical area they are representing, load measurements from Norway are used to construct the detailed models presented here. Further, Section 2.3 describes the generic demand flexibility model for long-term grid planning purposes. Finally, Section 2.4 describes a comprehensive tool for optimal long-term grid planning that incorporates the generic demand flexibility model. For brevity, the latter will be referred to as the *planning tool*.

2.1 | Modelling of individual residential demand flexibility resources

In the residential sector, the flexible resources can be classified based on their power and energy capacity, and ease of shifting. Temperature-controlled loads such as space heaters and electric water heaters (EWH) have high power and energy storage capacity. White goods such as cloth washing machine (CWM), cloth drying machine (CDM) and dish washing machine (DWM) have low energy capacity, but very high shiftability to any time of the day. They are classified as atomic loads due to their autonomous operation [20].

2.1.1 | EWH flexibility

EWH has quantifiable heat capacity, predictable demand and flexibility, and all-season availability. EWH is modelled as a general thermostatically controlled load (TCL) with temperature hysteresis described for each individual EWH l as (1) and (2) adopted from [21].

$$\frac{dT_{tl}}{dt} = \frac{1}{C_l R_l}\left(T_t^a - T_{tl} + S_{tl} R_l P_{tl}^m\right) \tag{1}$$

$$S_{tl} = \begin{cases} 1 & \text{if} \quad S_{(t-1)l} = 0 \quad \text{and} \quad T_{tl} \leq T_l^{\min} \\ 0 & \text{if} \quad S_{(t-1)l} = 1 \quad \text{and} \quad T_{tl} \geq T_l^{\max} \\ S_{(t-1)l} & \qquad\qquad\qquad\qquad\quad \text{Otherwise} \end{cases} \tag{2}$$

In general, the volume and power rating of EWH in a Norwegian single family house is 200 L and 2–3 kW [22]. EWH consumption data was collected from multiple single family houses in Norway for a duration of 285 days from March 2016 to February 2017 [23]. Data analysis of the smart meter data reveals that typical temperature hysteresis is 5°C. The EWH has a lower temperature threshold T^{min} of 70°C to avoid the growth of Legionella [24], and an upper threshold T^{max} which is 75°C. The typical value of thermal capacitance of the hot water tank is found to be 0.335 kWh/°C. The average demand profile for 24 h for a single family house is as shown in Figure 1. The EWH model in (1) can be modified to (3) by adding the heat demand to the ambient temperature loss as shown in (4):

$$\frac{dT_{tl}}{dt} = S_{tl}\frac{P_{tl}^m}{C_l} - \dot{T}_{tl} \tag{3}$$

where

$$\dot{T}_{tl} = \frac{1}{C_l R_l}(T_t^a - T_{tl}) + \dot{T}_t^{Load} \tag{4}$$

Today, EWH flexibility can be controlled by switching them OFF, only when the internal thermostat is ON. The internal thermostat will disconnect EWH during the temperature hysteresis. Therefore, EWH cannot be forced to switch ON during the temperature hysteresis period. The downward flexibility is achieved by forcing the EWHs to switch OFF, and the upward flexibility is achieved by using their rebound characteristics. The flexibility potential of EWH is characterised as available flexible power, flexible energy and resultant rebound at different hours of a day. EWHs can be switched OFF for a maximum duration of 2–6 h without violating user comfort [22], [25]. The duration depends on the size of the hot water tank and hot water demand. For the detailed flexibility model, EWH flexibility has been activated during every hour of a day for 1 h on the base profile and corresponding rebound is calculated. A group of 1000 EWHs are used for the simulation and calculation. Final values are normalised to per unit. A detailed analysis of flexibility activation on EWHs is available in [26]. Equations (2)–(4) are used to generate different discrete demand profiles with flexibility activation at all hours of the day, which includes the rebound effect due to temperature loss. The generated power profiles are used in (6) of the detailed flexible demand model in Section 2.2.

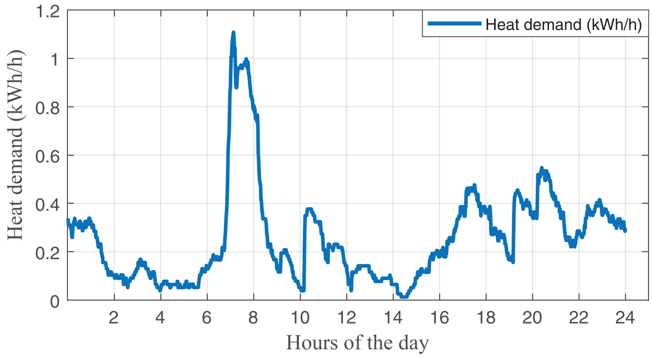

FIGURE 1 Average heat demand profile from a EWH at single family house

2.1.2 | Atomic loads flexibility

Unlike TCLs, atomic loads cannot be interrupted if they are already started and in operation. Interrupting their operation may affect their programmed operational sequence. Therefore, atomic loads that are started cannot be interrupted in order to move load to another hour. On the other hand, atomic loads can be shifted to any desired hour of the day, which is not possible with EWHs as they are bound to keep the water temperature within the limit. The probability distribution of an atomic load to start at different hours of the day and their demand profile are used to identify their flexibility potential [2]. The power consumption profiles for different modes of operation of cloth washing machines (CWM), cloth drying machines (CDM) and dish washing machines (DWM) are shown in Figure 2. Their probability to start at different hours of a day is shown in Figure 3. To have average load profile and their flexibility potentials, a sufficiently large number of cases have to be simulated. For the detailed flexibility model, simulation of a population

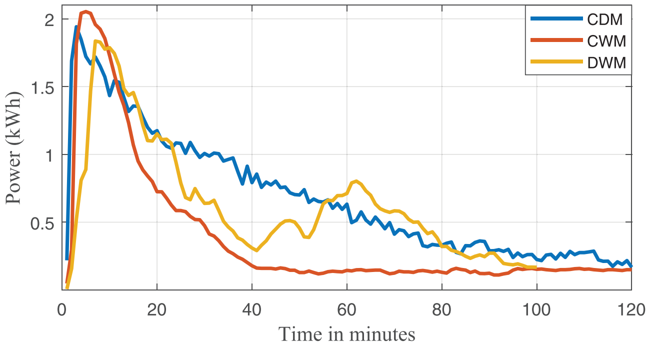

FIGURE 2 Average demand profile of atomic loads

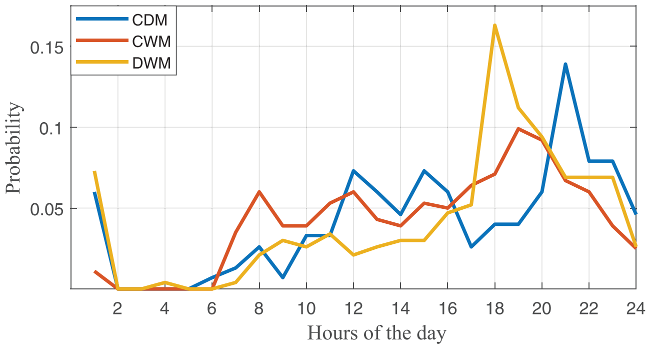

FIGURE 3 Probability of atomic loads to start at different hours of a day

of 1000 households was used, and the resultant profiles are normalised to per unit.

2.2 | Activation of flexible demand components in a detailed demand flexibility model

The activation of all the flexible load components must be scheduled over the operational planning horizon to get an aggregated demand flexibility at the relevant buses, which is useful for operation of the distribution grid. A detailed operational model is developed to model the optimal flexibility activation for managing congestions in the distribution grid and accurately estimate the operational costs and benefits. Its purpose in this article is to serve as a basis of comparison for the more coarse-grained grid planning tool introduced in the next section. The model represents the operational planning problem faced by a flexibility aggregator responsible for a set of buses downstream of the potential congestion. The aggregator is given forecasts of the (reference) load demand and a net exchange capacity by the distribution grid operator. The objective is to find the lowest cost activation of the flexible demand components such that the resulting load is lower than a net exchange capacity, thus avoiding costly load reduction or curtailment of the non-shiftable residual load.

The cost of flexibility activation as measured by compensation to the energy consumer per units of energy that is shifted in time is given by C^{SD}. For comparison with the generic model in Section 2.3, we also include the flexibility option of (voluntarily) reducing load, which is compensated at a cost of C^{nce} per unit of energy that is not consumed. Load curtailment represents forced reduction of load and is a slack variable which ensures feasibility of the optimisation model. In addition, the cost of load curtailment, C^{curt}, is added to the objective function and is typically two orders of magnitude higher than the marginal generation costs. The objective function is shown in (5). Note that load reduction and load curtailment apply to a residual component of the load demand that is not modelled as shiftable demand:

$$\min \sum_{t\in\mathcal{T}} \Delta T \left(\sum_{l\in\mathcal{L}} C_l^{SD} p_{tl}^{SD} + C_l^{nce} p_{tl}^{nce} + C_l^{curt} p_{tl}^{curt} \right) \tag{5}$$

Here, we will consider time steps ΔT of 1 h. The optimisation model combines the response of each load component $l \in \mathcal{L}$ by considering the profiles for activating each component for a given hour of the day $t \in \mathcal{T}$. The net shift up (SU) and shift down (SD) is calculated according to (6):

$$p_{tl}^{SU} - p_{tl}^{SD} = \sum_{a\in\mathcal{A}_t} \left(P_{tal}^{SD} \delta_{al}^{SD} + P_{tal}^{SU} \delta_{al}^{SU} \right) \qquad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \tag{6}$$

The shift profiles, $P_{tal}^{SU/SD}$, represent the load changes for load component l in hour t from shifting load in hour a. The activation of upward or downward shifting in hour a is given by $\delta_{al}^{SU/SD}$. The resulting net load from summing the contribution of all load components at the bus after flexibility activation is given by (7):

$$p_t^{flex} = P_t^{ref} + \sum_{l\in\mathcal{L}} \left(p_{tl}^{SU} - p_{tl}^{SD} \right) - p_t^{nce} - p_t^{curt} \qquad \forall t \in \mathcal{T} \tag{7}$$

The net load has to be lower than the net exchange capacity from the bus to the rest of the grid as shown in (8):

$$p_t^{flex} \leq P_t^{exch} \qquad \forall t \in \mathcal{T} \tag{8}$$

Furthermore, the load shifting is limited by the initial load for each load component, and the total energy shifted should be equal in both directions as shown in (9) and (10), respectively:

$$p_{tl}^{SD} \leq P_{tl}^{ref} \qquad \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \tag{9}$$

$$\sum_{t\in\mathcal{T}} p_{tl}^{SU} = \sum_{t\in\mathcal{T}} p_{tl}^{SD} \qquad \forall l \in \mathcal{L} \tag{10}$$

2.3 | Generic demand flexibility modelling for long-term planning purposes

The detailed model in Section 2.2 considers whether each individual flexibility resource should be activated for each hour. Explicitely modelling them would result in an intractable number of integer variables for large power systems with many buses and flexibility resources and long planning horizons. A generic demand flexibility model is therefore developed to represent the aggregated response per bus for a range of different demand flexibility resources. Aggregation reduces the number of variables and results in tractable models, which can include flexible demands in large scale grid planning studies.

The main novelty of this model, compared to the existing models in the literature reviewed in Section 1, is the two constraint formulations for capturing intertemporal dependencies introduced in Section 2.3.3. Different parameterisations of the generic demand flexibility model can be used to represent [27]: electric vehicles, industrial demand flexibility, residential demand flexibility, thermal loads, and hydrogen production as an industrial load. For each type of flexibility resource, parameter values must be appropriately chosen to represent their behaviour in a realistic manner.

The demand is specified for each bus, n, in the aggregated model as compared to each load component, l, in the detailed model. There are two types of electricity demand in the aggregated model, firm or flexible demand. Firm electric demand is modelled by a reference demand, P^{ref}_{tn}, and involuntary load curtailment, p^{curt}_{tn} to be activated in extreme case, and is modelled similarly as in Section 2.2.

For flexible loads, the generic demand flexibility model has two options for changing the net load: 1) voluntary load reduction (p^{nce}_{tn}) and 2) load shifting up (p^{SU}_{tn}) or down (p^{SD}_{tn}). The resulting net load after flexibility activation, p^{flex}_{tn}, for load at bus n at time t is shown in (11):

$$p^{flex}_{tn} = P^{ref}_{tn} + p^{SU}_{tn} - p^{SD}_{tn} - p^{nce}_{tn} - p^{curt}_{tn} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{11}$$

Additional constraints are added to obtain the desired behaviour for the different flexibility resources as described in the following paragraphs.

2.3.1 | Load reduction

Load reduction represents the permanent and voluntary reduction of load from the reference demand. The load reduction is constrained by an upper limit which is relative to the reference demand as shown by (12):

$$0 \le p^{nce}_{tn} \le P^{nce,\max}_{n} P^{ref}_{tn} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{12}$$

Activating load reduction has a cost, $C^{nce}_{n} p^{nce}_{tn}$, which is added to the objective function. The total reduction of consumed energy is represented as e^{nce}_{tn} for each time step in (13). The total energy reduction is limited by $E^{\text{nce,max}}_{n}$ defined over the time horizon T as shown in (14):

$$e^{nce}_{tn} - e^{nce}_{(t-1)n} = \Delta T \cdot p^{nce}_{tn} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{13}$$

$$e^{nce}_{tn} \le E^{\text{nce,max}}_{n} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{14}$$

2.3.2 | Load shifting

Load shifting implies that load is temporarily reduced or increased compared to the reference load demand. The total energy shifted up e^{SU}_{tn} and down e^{SD}_{tn} are defined in (15) and (16), respectively:

$$e^{SU}_{tn} - e^{SU}_{(t-1)n} = \Delta T \cdot p^{SU}_{tn} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{15}$$

$$e^{SD}_{tn} - e^{SD}_{(t-1)n} = \Delta T \cdot p^{SD}_{tn} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{16}$$

Energetically, the total amount of load shifted upward has to be equal to the total amount of load shifted downward at the end of the time horizon as shown in (17):

$$e^{SU}_{Tn} = e^{SD}_{Tn} \qquad \forall n \in \mathcal{N} \tag{17}$$

To consider appropriate bounds on the power consumption, the maximum load shifted at time t is limited using (18) and (19). The maximum load shifted varies with time dependent on the reference load.

$$p^{SU}_{tn} \le p^{SU,max}_{tn} = P^{SU,max}_{n} P^{ref}_{tn} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{18}$$

$$p^{SD}_{tn} \le p^{SD,max}_{tn} = P^{SD,max}_{n} P^{ref}_{tn} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{19}$$

These constraints give rise to a flexibility band $[P^{ref}_{tn} - p^{SD,\text{max}}_{tn}, P^{ref}_{tn} + p^{SU,\text{max}}_{tn}]$ around the reference demand P^{ref}_{tn}. The costs of load shifting are added to the objective function according to $C^{SU} p^{SU}_{tn}$ and $C^{SD} p^{SD}_{tn}$ for up and down shifting, respectively.

2.3.3 | Recovery and proximity constraints

Some types of demand flexibility has to recover in order to be utilised again or has automatic rebounds as discussed in Section 2. This is captured by the shifting profiles for each flexible demand component in the detailed model. For a more generic model for planning purposes, additional constraints can help capture some of the response characteristics from the individual flexible demand components in the aggregated demand flexibility model.

Two options for such constraints capturing temporal interdependencies are formulated for improving the generic demand flexibility model. As it is not obvious a priori which formulation produces the most realistic demand flexibility behaviour, this will be investigated in the case study in Section 3.

The first option is the recovery period constraints in (20) and (21). These constraints ensure that activated flexibility reduce the future potential flexibility activation for the duration of a *recovery period*. This is modelled by subtracting the load shifting activated during the recovery period leading up to time t from the maximum load shifting. We define the

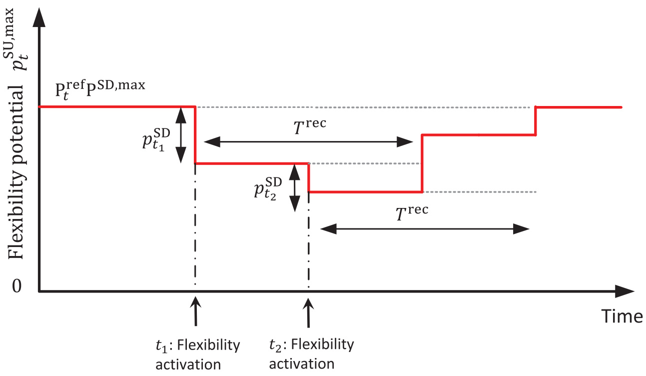

FIGURE 4 Temporal interdependencies as represented by constraints on available flexibility potential defined by a load recovery period

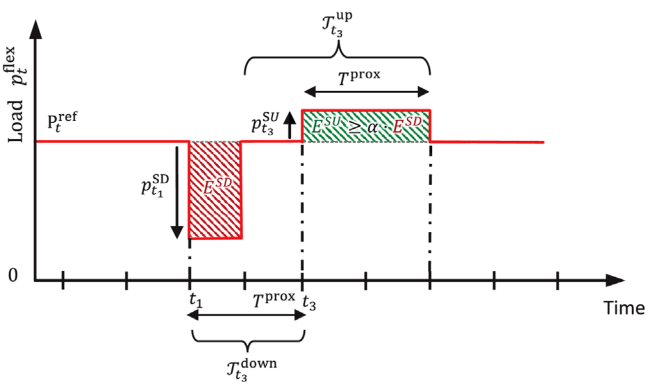

FIGURE 5 Temporal interdependencies as represented by proximity constraints for load shifting

set of times in the recovery period which affect time t as $\mathcal{T}_t^{rec} = \{t - T^{rec}, \ldots, t-1\}$:

$$p_{tn}^{SU} \leq p_{tn}^{SU,\max} - \sum_{j \in \mathcal{T}_t^{rec}} p_{jn}^{SU} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{20}$$

$$p_{tn}^{SD} \leq p_{tn}^{SD,\max} - \sum_{j \in \mathcal{T}_t^{rec}} p_{jn}^{SD} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{21}$$

The resulting constraints on the potential flexible demand available to be shifted is illustrated in Figure 4 for the case of downward demand shifting. The constraints in (20) and (21) are always tighter than (18) and (19), making those constraints redundant.

The second option is the *proximity constraint*, which can be used to model that flexible loads can have rebound effects after downward load shifting or that the energy must be consumed within some time, for example, running the washing machine within the day. This constraint ensures that some share of the upward shifting is activated in proximity to the downward shifting as formulated in (22) and illustrated in Figure 5. The downward shifting during period $\mathcal{T}_t^{down} = \{t - T^{prox}, \ldots, t-1\}$ should be accommodated by a share, σ^{prox}, of upward shifting in the period $\mathcal{T}_t^{up} = \{t - T^{prox} + 1, \ldots, t + T^{prox}\}$.

$$\sum_{j \in \mathcal{T}_t^{up}} p_{jn}^{SU} \geq \sigma^{prox} \sum_{j \in \mathcal{T}_t^{down}} p_{jn}^{SD} \qquad \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{22}$$

2.4 | Incorporating the generic demand flexibility model in a long-term grid planning tool

The generic flexibility model described in Section 2.3 has been incorporated in a comprehensive model for optimal long-term transmission and distribution grid planning [28, 29] developed in the FlexPlan project [30]. This is a large-scale stochastic mixed integer linear programming model for finding the optimal combination of planning candidates, including both investments in flexibility (either energy storage systems or enabling demand flexibility) as well as in traditional grid infrastructure for a given number of scenarios and planning years. For such a long-term planning tool to be computationally tractable, appropriate simplifications of the modelling of grid operation is an absolute necessity.

This article focuses on the operational modelling embedded in the grid planning tool. For detailed descriptions of all aspects of the full planning tool we refer to [28, 29], and here we only represent briefly those aspects most relevant for the purposes of this study. To be able to compare its representation of demand flexibility with that of the more detailed model presented in Section 2.2, we consider the operational costs and benefits over an operational planning horizon of a few days. The relevant parts of the model objective then takes a similar form as (23) for the detailed model:

$$\min \sum_{t \in \mathcal{T}} \Delta T \left[\sum_{g \in \mathcal{G}} C_g p_{tg} + \sum_{n \in \mathcal{N}} \left(C^{CU} p_{tn}^{SU} + C^{CD} p_{tn}^{SD} + C^{nce} p_{tn}^{nce} + C^{curt} p_{tn}^{curt} \right) \right] \tag{23}$$

The main difference from (23) is that there are no integer variables for flexibility activation and that the sum goes over all buses $n \in \mathcal{N}$ in the distribution grid. The terms $C_g p_{tg}$ represent power generation costs or power import costs.

The operational optimisation model embedded in the grid planning tool needs to capture the effect of voltage drop and reactive power flow in distribution grids. To keep the optimisation model linear, a linearised branch flow model for radial distribution grids has been implemented. Moreover, the model includes constraints to capture branch flow limitations and bus voltage magnitude limitations. The full mathematical formulation of the power flow model and all other constraints can be found in [28]. The optimisation model has been implemented in Julia/JuMP language [31] on the basis of the packages PowerModels.jl [32] and PowerModelsACDC.jl [33].

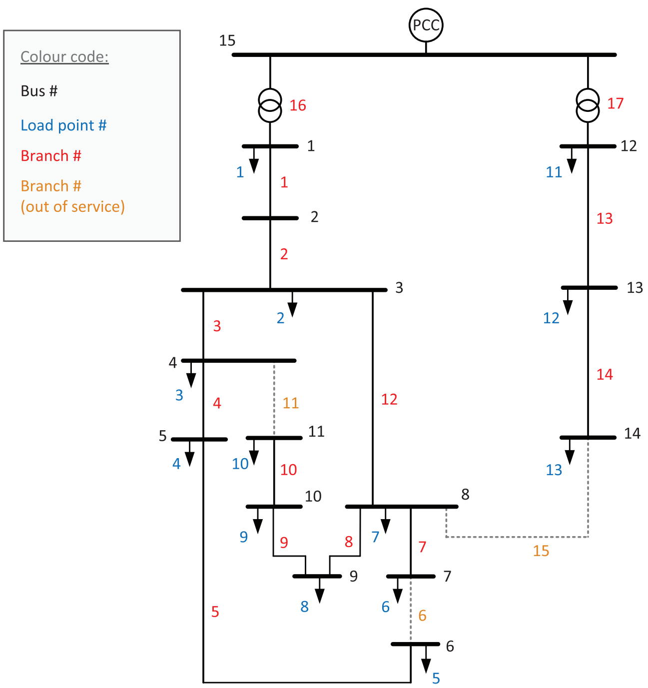

FIGURE 6 CIGRE medium voltage grid benchmark, based on [34]

3 | CASE STUDY

The flexibility representations of the *detailed operational model* and the *planning tool* are investigated using a test grid specified in Section 3.1. Further, Section 3.2 investigates the sufficiency of the flexibility modelling for the base case, whereas sensitivities to the representation of temporal interdependencies including rebound effects are investigated in Sections 3.3 and 3.4, respectively. We focus on investigating the operational costs and benefits as estimated by the flexibility models, but we briefly motivate the investigation and put it in the context of a grid planning problem in Section 3.1. The implications of the results for this grid planning problem are illustrated in Section 3.6.

We should also emphasize that the goal of this case study is not to present a comprehensive flexibility aggregation methodology but rather to combine selected available demand flexibility resources using a detailed model (with available, real data) to highlight some key considerations for representing aggregated demand flexibility in long-term planning models.

3.1 | Test grid and grid planning problem

The chosen test distribution grid is the CIGRE Medium Voltage (MV) distribution grid benchmark (European configuration) as shown in Figure 6 and further described in [34]. Load demand data from Norway is used to test the demand flexibility model for distribution grids, based on the original data of the CIGRE MV grid benchmark. Since the load time series are all for residential loads, the original data are modified to represent only residential load for all buses in the distribution grid. The power factor values are the same as for the residential component of the loads in [34]. The residential load in bus 1 is divided into the three load components based on the typical Norwegian residential load energy shares as shown in Table 1. EWH and atomic loads flexibility are aggregated in different ratio due to variations in their power and energy capacity [2].

TABLE 1 Load breakdown in bus 1, based on typical household electricity consumption [36]

Load component	Share (%)
Firm load	75.7
Water heater	19.0
White goods	5.3

All of the electricity in the distribution grid is imported from the upstream power system at bus 15. The power system is represented by a large generator with a marginal cost of 30 €/MWh. The power transfer capacity at the transformer feeding the feeder connected to bus 1 is reduced from 25 MW in the CIGRE MV benchmark data set to 15 MW such that this becomes a limiting restriction in the grid. Simply put, the grid planning problem is the choice between (a) investing in a transformer with larger power transfer capacity (25 MW) and (b) utilising demand flexibility. For the grid investment alternative (a), we assume a a transformer lifetime of 40 years, linear depreciation, an analysis horizon of 10 years, and a discount rate of 4%. Using information in [35], we estimate a transformer investment cost of 600 k€ and use the net present value method to calculate an annuity of the investment of 36 494 € . In other words, annual operational costs due to flexibility activation need to be below this value for the flexibility alternative (b) to be cost-effective. The case study will investigate how the estimate for the operational cost depends on the flexibility model.

For simplicity of presentation, and to allow a transparent comparison of the demand flexibility models, the case study is designed so that we can focus on the demand flexibility at one of the buses in the grid. We focus on the first bus on the longest feeder, namely bus 1. The load demand at this bus dominates the load demand contributions further out in this feeder of the CIGRE MV grid benchmark. For simplicity, the load demand at the other load points is therefore assumed to firm demand.

Although voltage magnitude limits are also considered by the planning tool in the case study, in this particular case they do not impose binding constraints on the capacity of the distribution grid to supply the load demand. (We refer to [28] for a variation of the case study where voltage restrictions become limiting for the capacity of the distribution grid.)

3.2 | Base case results

The total residential load from the detailed demand flexibility model is obtained by combining the activation of different flexible loads at bus 1. The results from detailed model are used to set the parameters for the generic flexible demand model in the

TABLE 2 Input parameters for the demand flexibility model

Parameter	Description (Ref unit)	Selected value
$E^{nce,max}$	Maximum accumulated voluntary load reduction (MWh)	1000
$P^{nce,max}$	Superior bound on voluntary load reduction (p.u. ∈ [0,1])	1
$P^{SU,max}$	Superior bound on upward demand shifted (p.u. ∈ [0,1])	0.29
$P^{SD,max}$	Superior bound on downward demand shifted (p.u. ∈ [0,1])	0.164
E^{SD}	Maximum accumulated load shifted downward during time horizon (MWh)	124.2
T^{rec}	Recovery period for demand shifting (h)	0
T^{prox}	Proximity period for demand shifting (h)	0
C^{nce}	Compensation for voluntary demand reduction (€ /MWh)	200
C^{SU}	Compensation for upward demand shifting (€ /MWh)	0
C^{SD}	Compensation for downward demand shifting (€ /MWh)	20
C^{curt}	Compensation for involuntary demand reduction (€ /MWh)	2000

planning tool. For example, the resulting maximum value for upward and downward load shifting from the detailed model, which is 0.29 and 0.164 p.u. of the reference load, respectively, for this case, become the input parameters for the generic flexible demand model in the planning tool. Similarly, the total load shift for the simulation period in the detailed model gives the value for the relevant parameter in the planning tool, which is set to 124.2 MWh. In the following, a simulation period of 48 h is considered to illustrate the impact of flexibility modelling choices. A summary of the parameters chosen for the generic demand flexibility model for this case study is shown in Table 2. (For detailed information on estimations of flexibility costs, we refer to [27].) The cost for upward shifting (c^{SU}) is set to zero to avoid double-counting of the flexibility activation cost since demand shifted downward at any give time needs to be shifted upward again due to (17).

Initially, the recovery period and proximity constraints are disabled. The resulting net load after activating demand flexibility for the detailed model and the planning tool are compared in Figure 7. The reference load and the net exchange capacity from bus 1 represent the default state and limits of the distribution grid. The net exchange capacity is calculated by subtracting the loads further along the radial of bus 1 from the import capacity of the transformer connecting this radial to the transmission grid. Since the reference load exceeds the net exchange capacity much of the time, replacing the transformer (i.e. grid reinforcement) would be necessary in the absence of demand flexibility as an alternative.

The resulting load profile from the detailed model is either close to the reference load or the net capacity. This is because

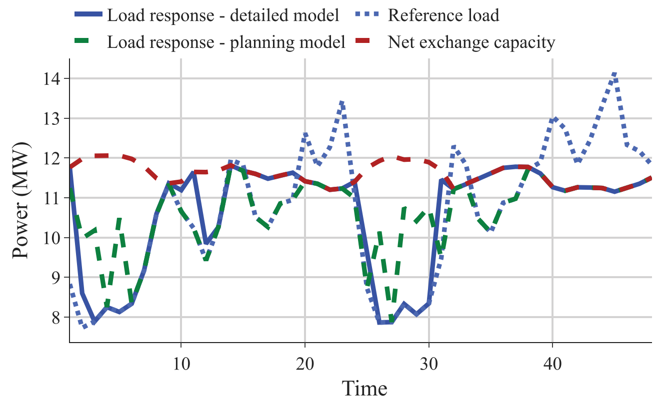

FIGURE 7 Resulting load profiles from the planning and detailed model compared to the reference load and the exchange capacity to the load point (bus 1). (Net capacity is calculated as the transmission capacity to the bus minus the further down the radial of bus 1.)

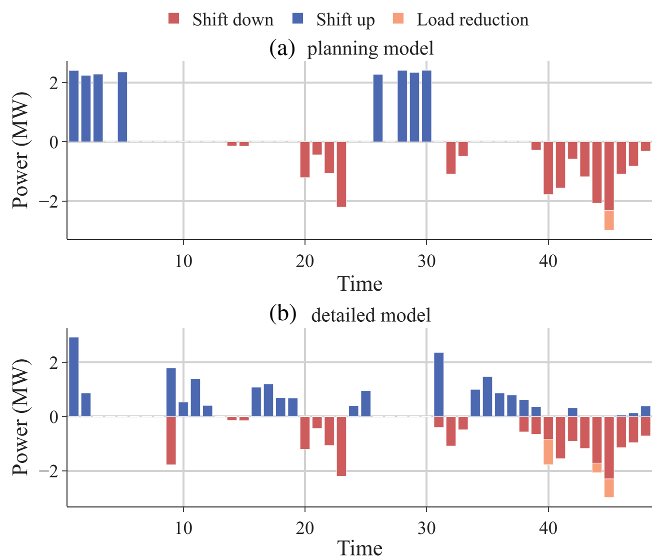

FIGURE 8 Load shifting and reduction for the flexible load in bus 1, from the planning tool (top) and the detailed load flexibility model (bottom)

the water heater has a rebound effect as this is a TCL, such that the corresponding upward load shifts are closer to the respective downward load shifts. The planning tool tends to increase load at night when the load is generally lower. In the base case, the load from the planning tool is different from the detailed model as it does not have any representation of the rebound effect. While the net profiles are a little different, both are below the net exchange capacity (Figure 7).

The load shifting for the two different models are shown in Figure 8. Upward shifting is more concentrated for the planning tool than the detailed model. Significant amounts of the upward shifting in the planning tool occurs in the beginning of the time period. There is also a greater distance from the upward shift to the downward shift in the planning tool compared to the detailed model. Distributed upward shifting and less time between downward and upward shifting in the detailed model

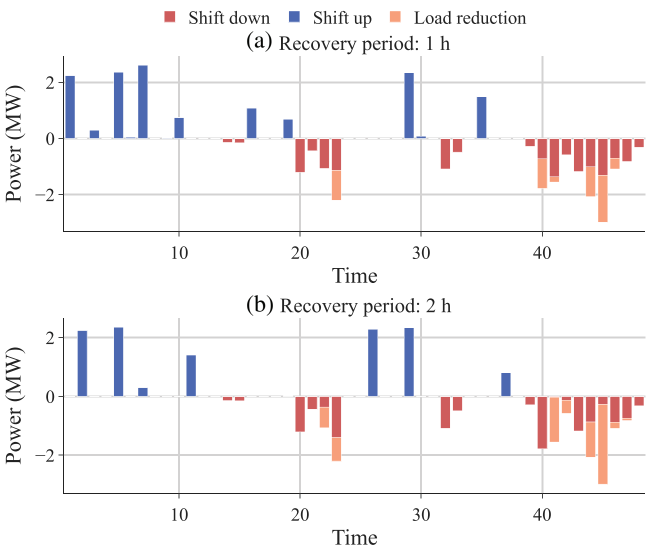

FIGURE 9 Load shifting and reduction with recovery period of 1 and 2 h for the recovery period constraint

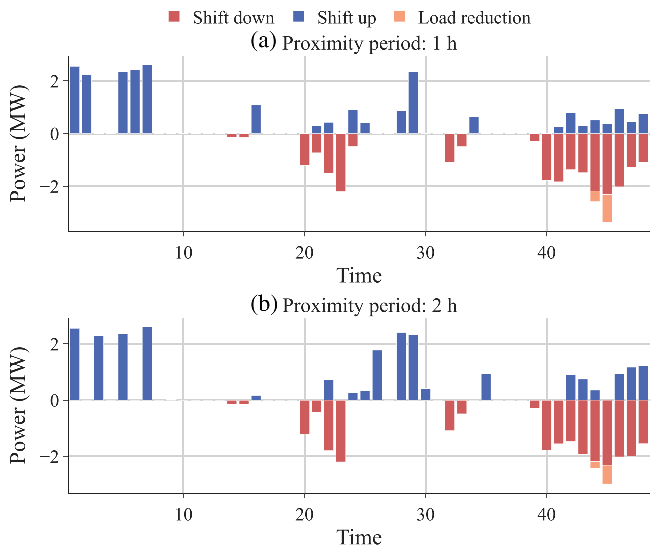

FIGURE 10 Load shifting and reduction with proximity periods of 1 and 2 h

are results of the detailed profiles for shifting of water heater and white goods loads. The detailed model distributes the load shifting over several hours according to the load shift profile, while the planning tool assumes that the effect of one load shifting activity can be concentrated to 1 h. The detailed model is also able to account for the fact that upward shifting for the water heater is an automatic rebound from reducing the water heater load, such that it can only happen after the downward shift.

Both models have the same net shift down as this is equal to the amount the reference load exceeds the net exchange capacity. However, the detailed model shifts demand both up and down at the same time. This is to control the rebound from the water heater which lead to a forced shift upward. Thus, it can be favorable to shift white goods down when the rebound occurs.

The detailed model results in a higher total load reduction than the planning tool. This is caused by limited downward shifting at these specific times from the load profile of the water heaters and white goods. In the planning tool, the maximum shifting is represented in a simplified way as a proportion of the reference demand. Thus, the planning tool is not able to accurately represent the maximum demand flexibility at all times since the share of the reference load which is controllable is not constant.

3.3 | Impact of the recovery period constraints

The impact of the recovery period constraints on the outcome of the planning model is tested by setting the recovery periods to 1 and 2 h as shown in Figure 9. All other parameters are kept at their base case values.

Increased recovery periods lead to more distributed upward shifting. The upward shifting is more similar to the detailed model results for a recovery period of 2 h. However, the recovery period constraints lead to excessive load reduction instead of downward load shifting. The reason is that the recovery period constraints reduce the potential for load shifting in consecutive hours when the reference load demand exceeds the net exchange capacity. The reduced total downward load shifting leads to reduced total upward load shifting, such that there is significantly less load shifting in total when the recovery period constraint is used.

3.4 | Impact of the proximity constraint

The recovery period constraint is replaced by the proximity constraint and the impact of this constraint is evaluated. The value of the proximity parameter σ is set to 0.6, which is found to give the most similar costs compared to the detailed model after testing values between 0 and 1 with an increment of 0.1 in combination with proximity periods of 1, 2 and 3 h. Longer proximity periods were also tested without resulting in more similar costs compared to the detailed model. While this parameter testing is not exhaustive, it is considered sufficient for illustrating the impact of this constraint. Setting σ to 0.6 means that downward shifting of demand will result in at least upward shifting equal to 60% of the downward shifted energy within the proximity period. The impact of the proximity constraint in (22) on the resulting load shift is shown in Figure 10 for recovery periods of 1 and 2 h.

The upward load shifting is more distributed compared to the original load shifting from the generic demand flexibility model in Figure 8. The proximity constraints do also lead to simultaneous upward and downward demand shifting, similar to the detailed model but a bit more frequently. In the detailed model,

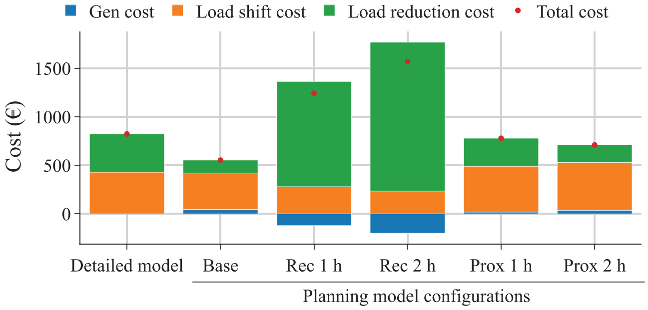

FIGURE 11 Comparison of costs from load shifting and load reduction from the different demand flexibility models. Changes in generator costs from the detailed model solution are added to the planning tool bars

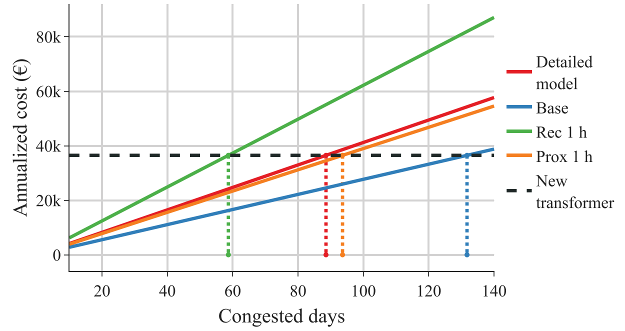

FIGURE 12 The annualised cost of investing in a new transformer compared to purchasing flexibility from flexible loads as a function of the number of days per year with transformer congestions. The break-even points are indicated on the x-axis for the different demand flexibility models

this is to control the rebound of the water heaters, while here it is the result of the modelling.

Load reduction is higher than for the base case configuration of the generic demand flexibility model, which is more accurate according to the detailed model. Increasing the proximity period from 1 to 2 h increases the load shifting and reduces the load reduction, which is less similar to the detailed model results.

For planning purposes, the most important outputs of the operational model are the profiles for net flexible load and total costs for load shifting, reduction and curtailment. The net load shifting is often equal to the detailed model in the periods where some extra simultaneous upward and downward shifting occur. The advantage of the simultaneous shifting is that it reduces the demand flexibility such that the generic demand flexibility model is able to capture some of the more expensive load reduction.

3.5 | Comparing operational costs for different demand flexibility modelling choices

The operational costs due to demand flexibility estimated with the different planning tool configurations are compared with the costs estimated with the detailed model in Figure 11. These operational costs include costs from load shifting and load reduction. In addition, the difference in generation costs from the detailed model are included for the results for the planning tool. (Because the total operational costs are dominated by generation costs, only the difference is illustrated for the generation costs in this figure.)

The base configuration of the planning tool underestimates the operational costs to 70% of detailed model costs as it overestimates the demand flexibility. On the other hand, the recovery period constraints underestimate the demand flexibility, which leads to high levels of load reduction. Load reduction is more expensive than load shifting and is typically the last resort before (involuntary) load curtailment. The excessive load reduction due to the recovery period constraints with 1- and 2-h recovery periods results in an overestimation of the load reduction costs by a factor of 2.8 and 3.9 compared to the detailed model.

The impact of the proximity constraint on load shifting gives a better result than the recovery period constraints. The proximity constraint is able to avoid excessive load reduction and keep the total amount of shifting similar to the base case results. The total costs related to load shifting and load reduction are closer to the detailed model when the proximity constraints are included compared to the base configuration. A proximity period of 1 h gives total costs, which are 96% of the detailed model costs. Compared to the detailed model, the costs are slightly shifted toward load shifting (+9.9%) rather than load reduction (-26.8%). Increasing the proximity period further leads to overestimation of the demand flexibility and lower costs.

3.6 | Implications for the grid planning problem

The operational cost for the 2 days are extrapolated in Figure 12 to illustrate the implications that the different flexible demand models will have on grid planning decisions. In practice, transformer congestions that require flexibility activation will only occur for a number of days throughout the year. For simplicity we assume that the operational costs estimated in Figure 11 are representative for these congested days. For the rest of the year, no operational costs due to flexibility activation are incurred. The annual flexibility costs as a function of a number of congested days are compared to the annualised investment costs for a new transformer.

Using the operational costs from the detailed model, 89 congested days or more are needed for the investment in a new transformer to be profitable over using demand flexibility. In comparison, the base model for demand flexibility overestimates the break-even point for transformer investment at 132 days with congestions. In other words, the less detailed base model overestimates the benefits of demand flexibility as an alternative to transformer investments. According to the detailed model, the annual operational costs will be 148% of the annualised transformer investment costs if the transformer is congested 132 days per year. The proximity constraints for flexible demand modelling gives the closest break-even point to the detailed model at 94 days.

4 | CONCLUDING REMARKS

Based on the investigations in the previous section, we can summarize some insights about the behaviour and operational benefits of demand flexibility according to (i) the generic demand flexibility model for planning purposes and (ii) the detailed operational model for individual flexibility resources. Without additional constraints to represent temporal interdependencies, the generic flexibility model generally overestimates the flexibility potential. This is because the detailed model effectively has more constraints: It represents (i) rebound effects, (ii) realistic load profiles of flexible demand components, and (iii) the fact that the flexibility potential realistically does not vary in proportion to the total reference load demand. This implies that a too simple model of demand flexibility may overestimate its benefits as an alternative or supplement to grid investments.

On the other hand, the detailed flexibility model also has additional degrees of freedom in the sense that it can arbitrage between individual flexibility resources with different characteristics that are connected to the same bus. For example, loads for white goods can be shifted to counteract the rebound effect at the same time step for the electric water heaters.

The behaviour of demand flexibility as represented by the planning tool becomes more realistic when the proximity constraints are included. This formulation seems to be better suited to model demand flexibility in long-term planning models than the recovery period constraint. Possible modifications to the recovery period constraint should be considered such that the shifting capacity is not reduced too much. One alternative is to reduce the shifting capacity by a predetermined fraction of the load shifted during the recovery period instead of the sum of all load shifted as in (20) and (21).

Both the recovery period constraints and the proximity constraints add new parameters that need to be determined for long-term grid planning studies. Both these time parameters and the parameters for maximum upward and downward demand shifting can be used to control and calibrate the effective flexibility potential to avoid that it gives too optimistic or too conservative estimates for the operational benefits of flexibility when compared with grid reinforcement. Presenting a model calibration methodology was not the aim of this article, but future work could investigate methods for determining the parameter values for the generic demand flexibility model that best represent the characteristics of different individual flexibility resources. Here, we focused some specific examples (water heaters and white goods), and there is ample scope of future research considering other flexibility resources (e.g. various industrial loads, space heating, electric vehicles etc.).

An interesting extensions of this work would be to extend the models demonstrated here for residential demand flexibility in distribution grids to larger-scale power system studies. Considering the operational benefits of demand flexibility on a national or regional level would require a higher level of aggregation and including other flexibility resources, load demand sectors etc.

NOMENCLATURE

Indices

- l Load (for the detailed model)
- g Generator
- t Time
- a Time (at which flexibility was activated; for the detailed model)
- n Bus

Sets

- $\mathcal{L}$ Loads (for the detailed model)
- $\mathcal{N}$ Buses
- $\mathcal{T}$ Time steps
- $\mathcal{A}_t$ Time steps affected by activation of load shifting in time t
- $\mathcal{T}_t^{rec}$ Time steps in recovery period of load shifted in time t
- $\mathcal{T}_t^{up/down}$ Time steps for upward/downward load shift in proximity period of time t

Variables

- p_{tg} Generation (MW)
- $p_{tl}^{SU/SD}$ Load shifted upward/downward (MW)
- $\delta_{al}^{SU/SD}$ Activation of upward/downward load shift (binary)
- p_{tl}^{nce} Voluntary load reduction (leading to energy not consumed; for the detailed model) (MW)
- p_{tn}^{nce} Voluntary load reduction (leading to energy not consumed; for the planning model) (MW)
- e_{tn}^{nce} Accumulated energy not consumed (voluntary) (MWh)
- p_{tl}^{curt} Load curtailed (not voluntary; for the detailed model) (MW)
- p_{tn}^{curt} Load curtailed (not voluntary; for the planning model) (MW)
- p_t^{flex} Net load after activation of demand flexibility (MW)
- $e_{tn}^{SU/SD}$ Accumulated energy shifted upward/downward (MWh)
- $p_{tn}^{SU/SD,max}$ Maximum load shift upward/downward (MW)

Parameters

- T_{tl} Water temperature (°C)
- T_t^a Ambient temperature (°C)
- C_l Thermal capacitance (kWh/°C)
- R_l Thermal resistance (°C/kW)
- P_l^m Rated power consumption (kWh)
- S_l ON/OFF control status (binary)
- T_l^{min} Minimum temperature threshold (°C)

T_l^{max}	Maximum temperature threshold (°C)
$\dot{T}_{tl}$	Rate of temperature change due to hot water demand and ambient loss (°C/min)
$\dot{T}_t^{Load}$	Rate of temperature change due to hot water demand (°C/min)
C_g	Cost of generation (€ /MW)
C^{SD}	Cost of shifting load downward (€ /MW)
C^{nce}	Cost of energy not consumed (voluntary load reduction) (€ /MW)
C^{curt}	Cost of load curtailment (not voluntary) (€ /MW)
ΔT	Length of time steps
$P_{tal}^{SU/SD}$	Upward/downward load shift profile for activation in hour a (MW)
P_t^{ref}	Reference profile for load (MW)
P_t^{exch}	Exchange capacity (MW)
$P^{nce,max}$	Maximum voluntary load reduction share (p.u.)
$P^{SU/SD,max}$	Maximum share of load shift upward/downward (p.u.)
$E_n^{nce,max}$	Maximum accumulated voluntary load reduction (MWh)
σ^{prox}	Share of downward load shift that must be compensated by upward load shift within the proximity period (p.u.)

AUTHOR CONTRIBUTIONS

Espen Flo Bødal: Conceptualization, data curation, formal analysis, investigation, methodology, software, visualization, writing - original draft. Venkatachalam Lakshmanan: Data curation, methodology, validation, writing - original draft. Iver Bakken Sperstad: Conceptualization, investigation, methodology, software, validation, writing - original draft. Merkebu Zenebe Degefa: Conceptualization, methodology, validation, writing - original draft. Maxime Hanot: Conceptualization, methodology, validation, writing - review and editing. Hakan Ergun: Conceptualization, methodology, software, validation, writing - original draft. Marco Rossi: Methodology, validation, writing - review and editing.

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CONFLICT OF INTEREST

The authors have declared no conflict of interest.

DATA AVAILABILITY STATEMENT

Data subject to third party restrictions.

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