Review

Comparative analysis of tertiary control systems for smart grids using the Flex Street model

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A R T I C L E I N F O

A B S T R A C T

Various smart grid control systems have been developed with different architectures. Comparison helps developers identify their strong and weak points. A three-step analysis method is proposed to facilitate the comparison of independently developed control systems. In the first step, a microgrid model is created describing demand and supply patterns of controllable and non-controllable devices (Flex Street). In the second step, a version of Flex Street is used to design a case, with a given control objective and key performance indicators. In the last step, simulations of different control systems are performed and their results are analysed and compared. The Flex Street model describes a diverse set of households based on realistic data. Furthermore, its bottom-up modelling approach makes it a flexible tool for designing cases. Currently, three cases with peak-shaving objectives are developed based on scenarios of the Dutch residential sector, specifying various penetration rates of renewable and controllable devices.

The proposed method is demonstrated by comparing IntelliGator and TRIANA, two independently developed control systems, on peak reduction, energy efficiency, savings and abated emissions. Results show that IntelliGator—a real-time approach—is proficient in reducing peak demand, while TRIANA—a planning approach—also levels intermediate demand. Both systems yield benefits (€5–54 per household per year) through reduced transport losses and network investments in the distribution network.

1. Introduction

Future energy scenarios of the Netherlands take into account a shift towards more distributed energy resources (DER), including renewable power technologies [1]. The introduction of technologies such as wind turbines and photovoltaics brings about issues concerning intermittency and overproduction [2,3]. To help mitigate these issues, local demand response (DR) and energy storage may be considered [4].

Integrating the DR and storage solutions requires an energy management system for smart grid control, that can respond to fluctuating demand and supply through direct-load control [5]. Different control architectures have been developed, which exhibit different characteristics (Section 2.1). The evaluation and comparison of control systems is useful for developers, as they can more effectively recognise strong and weak points of their systems. Different methods of evaluation are currently used (Section 2.2).

In our research, a new analysis method is proposed (Section 3) that is able to compare independently developed control systems using the Flex Street model (Section 4). The analysis method is demonstrated by designing three exemplary cases (Section 5) and comparing the IntelliGator and TRIANA control systems (Section 6).

2. Related work

2.1. Control architectures

Architectures of control systems are usually discussed within the context of microgrids, i.e. sections of the low voltage

distribution network containing loads as well as DER. Microgrids focus on autonomy by matching supply and demand internally. Achitectures are often designed as a multi-agent system, which fits the characteristics of microgrids as distributed, dynamic, scalable and modular systems [6]. Three levels are discerned in the operation of microgrid control [7,8]. Primary and secondary control are concerned with safeguarding and optimising power quality, respectively.[1] This study focuses on the evaluation of tertiary control systems.

Tertiary control replaces the actions of secondary control by scheduling device dispatch according to some optimisation process (usually economic). This requires communication between local controllers (i.e. devices). A central controller is commonly instituted to create a hierarchical communication topology. However, different governance structures may appear depending on the roles of the controllers [13].

In a hierarchical system, a central controller optimises the scheduling and issues commands to local controllers, thus leading to centralised control. If instead of commands, only requests are sent for a cap on quantity or price, control becomes more decentralised.

In a market system, local controllers compete for resources, while a central controller acts as auctioneer (i.e. mediated trade). Provided that all market participants are perfectly competitive, this leads to decentralised control [14]. When a central controller can (and does) set market prices, this leads to more centralised control.

An alternative governance structure to hierarchies and markets is a co-operative network [15]. Co-operative networks are less guided by a formal structure of authority, depending on reciprocal communication and exchange (i.e. direct trade). This form of governance has also received attention in the context of virtual power plants [16]. The role of a central controller, if any, would be limited to that of a bulletin board listing offers from available devices [17,18].

2.2. Evaluation studies

The most common evaluation methods for individual (tertiary) control systems are case study simulations and field trials; both are usually defined in the context of microgrids. Evaluation studies exist for all three types of control architectures, such as in Refs [19–23] (hierarchy-based), Refs [24–27] (market-based) and Refs [28–30] (network-based). Performance indicators vary considerably, or, in some studies, are absent completely.

Several studies also provide a comparison of different control systems, all of which using case study simulations. Three different analysis methods are used for these comparisons (Fig. 1):

1. independent simulations of systems operating on different cases, which yields a qualitative comparison (e.g. Ref. [31]);
2. simulations operating on equivalent cases, which gives a quantitative comparison (e.g. Refs. [32,5]); and
3. co-simulations of control systems within the same case, which enables a quantitative assessment of interoperability, competition and emergent properties (e.g. Ref. [33]).

The first two methods are mainly used to evaluate microgrid control, while the third method is used to evaluate virtual power plant control.

Although evaluation studies have made attempts to provide standardised cases, they either show a limited scope (i.e. a small or
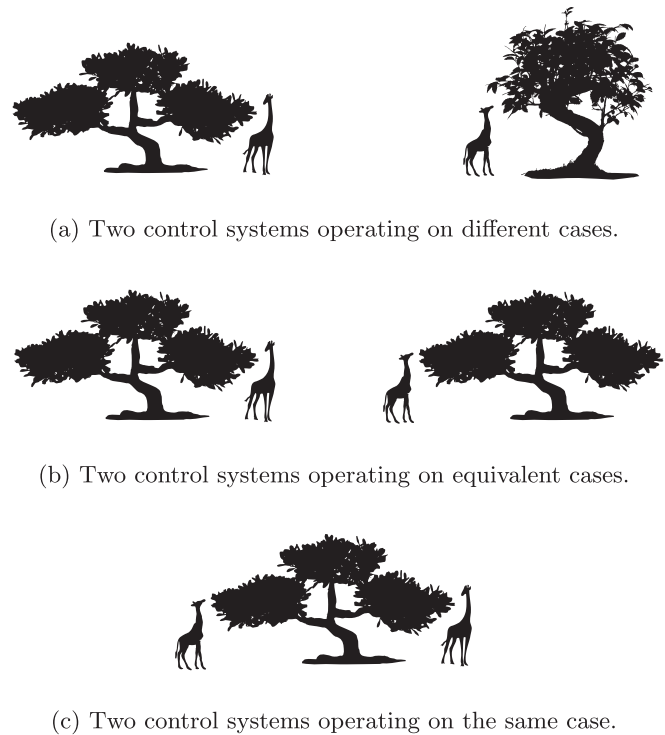

(a) Two control systems operating on different cases.

(b) Two control systems operating on equivalent cases.

(c) Two control systems operating on the same case.

Fig. 1. Behavioural comparison methods depicted by giraffes feeding on savannah trees.

uniform device population) or have not actually been subjected to multiple control system architectures. The present study implements the second analysis method. However, it is explicitly set up to facilitate the comparison of independently developed control systems. Furthermore, our case study aims to resemble a realistic setting for the operation of smart grid control systems, describing a large and diverse device population.

3. Analysis method

The proposed method consists of three steps: In the first step, the Flex Street model generates versions of a residential microgrid. In the second step, a case is made by assigning an objective to these microgrids, and defining key performance indicators (KPI) for the control systems. In the final step, different control systems are simulated in a case study, and the output of the simulations is analysed using the KPI.

A clear separation between the assembly of a case and the simulations of developed control systems has two benefits: it enables the use of pre-existing simulation environments (simulators) owned by participating developers, and it facilitates the creation of standardised cases for comparison studies.

4. Flex Street

The Flex Street model represents a microgrid of 400 houses connected to the main gas and electricity grid. The houses are fitted with a selection of distributed energy resources (DER), storage options and controllable loads (Fig. 2). Submodels of all devices are described in Section 4.1–4.3. The majority of devices is modelled in a bottom-up approach to create flexibility in case design. Flex Street currently describes the demand and supply patterns (electricity and heat) of all devices within the microgrid for one year, using a time step of 15 min. Devices were modelled with prognostic

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[1] Different architectures of primary and secondary control are discussed in Refs. [9,10] and [7,11,12], respectively.

(a) Including all renewable and controllable devices.
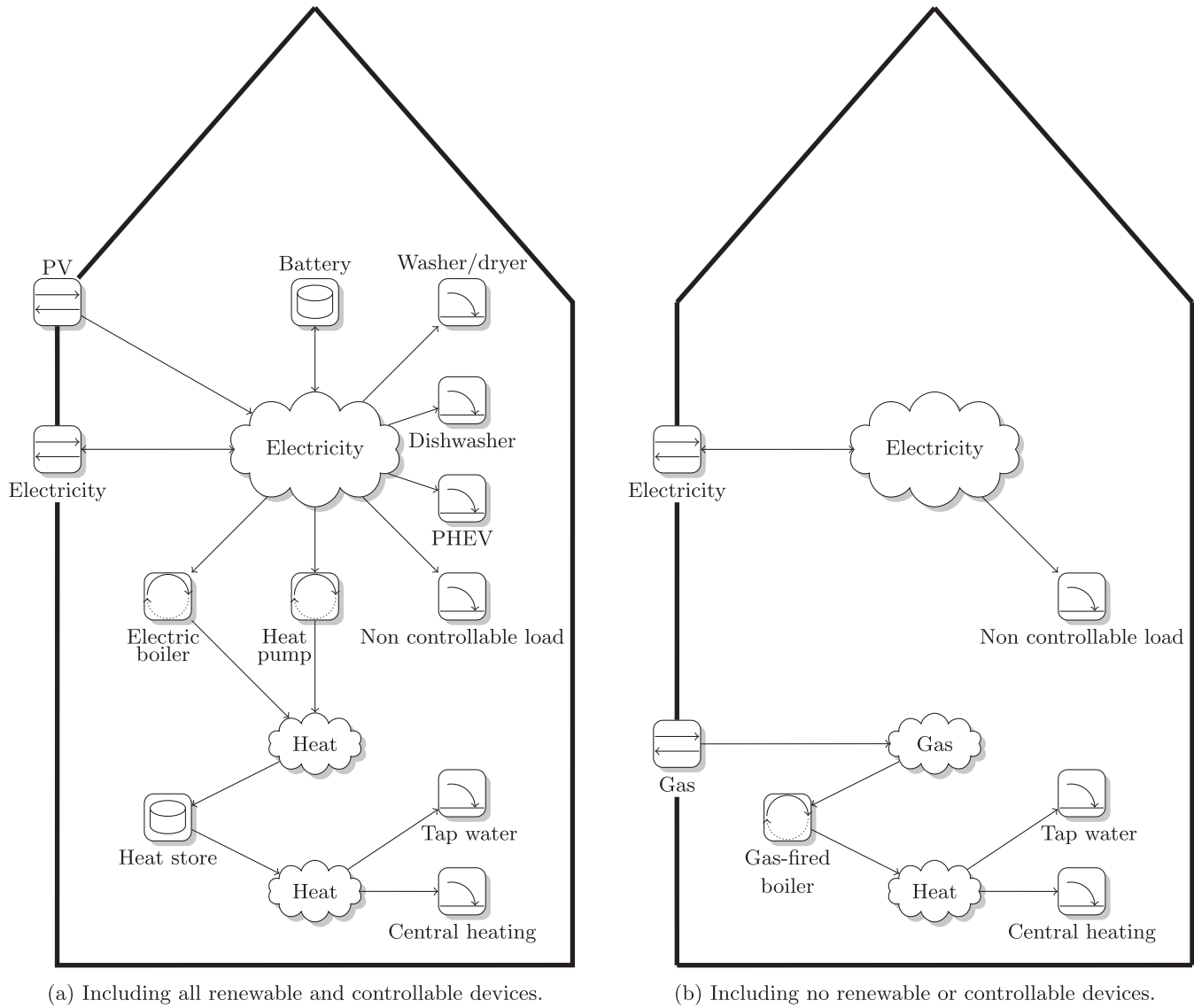
(b) Including no renewable or controllable devices.

Fig. 2. Energy streams of houses modelled in Flex Street.

consumption/production data and usage statistics that describe residential use in 2050, for a neighbourhood with terraced houses in the Netherlands.

Different versions of Flex Street can be generated by defining different device populations. We defined three scenarios for renewable and controllable devices, which describe their penetration in Dutch terraced houses in 2050 (Table 1). Penetration rates were separated into pessimistic, moderate and optimistic rates. A fourth scenario assuming zero penetration rates was included as a reference. Fixed penetration rates were used for other devices. Batteries were allocated only to houses with PV units, and a non-controllable gas-fired heating system was assumed for houses without an electric heating system.

4.1. Controllable device submodels

Characteristics of controllable devices are given in Table 2. Parameters of storage devices and DER are identical for each house. Battery efficiency is defined as round-trip efficiency, whereas the efficiency of thermal storage depends on a relative loss over time. Heat pumps come installed with a less efficient backup heater.

Table 1

Penetration rates of modelled devices in Flex Street. More uncertain rates (i.e. for controllable and renewable devices) have been defined in different scenarios.

(a) Scenario dependent penetration rates, separated into pessimistic, moderate and optimistic rates. An electric heating system is comprised of a thermal storage unit, a heat pump and an electric backup heater.

Scenario	Penetration rate (%)					
	PV units	Batteries	Electric heating systems	Washer/dryers	Dishwashers	PHEVs
Reference	0	0	0	0	0	0
Pessimistic	5	0	0	20	20	10
Moderate	15	5	50	60	60	50
Optimistic	30	20	100	100	100	90

(b) Scenario independent penetration rates.

Penetration rate (%)

Non-controllable electricity demand	Heating heat demand	Domestic heat demand			
		Showers	Baths	Bathroom taps	Kitchen taps
100	100	100	36	100	100

Table 2
Model parameters of controllable devices in the Flex Street microgrid. Consumption/production data and usage statistics have been used that describe residential use in the Netherlands in 2050 (sources in text).

(a) Characteristics of storage devices and converters.

Type	Rated power	Capacity	Efficiency
Batteries	0…3.4 kW	8.5 kWh	90%
Thermal storage	0…∞ kW$_{th}$	8 kWh$_{th}$	99.95%/(15 min)
Heat pumps	10 kW$_{th}$	–	COP$_{heat\ pump}$ = 5
Backup heaters	0…∞ kW$_{th}$	–	COP$_{backup}$ = 1

(b) Characteristics of devices in the demand response category.

Type	Rated power	Capacity	Start time	Cycle length	Max run time
Washer/dryers	926 ± 212 W	–	Uniform distribution	3 h	24 h
Dishwashers	275 ± 51 W	–	8am ± 0.5 h (25%)	2 h	4 h
			1pm ± 0.5 h (25%)	2 h	4 h
			6pm ± 0.5 h (50%)	2 h	13 h
				Min run time	Deadline
PHEVs	0…3.7 kW	3 kWh (33%)	5.30pm ± 1 h	0.8 h	7am ± 1 h
		6 kWh (33%)		1.6 h	
		12 kWh (33%)		3.2 h	

Several types of DR devices were modelled: appliances and plug-in hybrid electric vehicles (one-way distribution). Washer/dryers and dishwashers were given a constant demand profile. The rated power of these devices is described by a normal distribution, generating a unique profile for each house [34]. Washer/dryers are used 4, 6 or 7 days per week depending on the number of occupants (2, 3 or 4+ persons, respectively) [35]. Dishwashers are used 7 days per week. Start times of washing cycles are described by probability distribution functions, from which stochastic variations are derived (Fig. 3). A uniform distribution was used for washer/dryers. Dishwashers are turned on either in the morning, noon or evening, with a respective likeliness of 25, 25 and 50% [35]. Control systems may shift start times within a limited time interval. Washer/dryers are non-preemptible. Dishwasher programmes are interruptible after 1 and 1.5 h. A fixed maximum run time was set for each start time distribution.

Plug-in hybrid electric vehicles (PHEVs) are fully preemptible. Instead of a given demand profile, we defined only a maximum power flow. Three types of PHEV were modelled with an equal market share and a different effective battery capacity [36]. It was assumed that the cars have to be fully recharged every day. Start times and end times of charging were described by normal distributions around 5.30pm and 7am, respectively (Fig. 3) [37].

4.2. Non-controllable device submodels

Devices that are not modelled explicitly (e.g. freezers) were assumed non-controllable and their loads were aggregated in each house. Datasets for non-controllable electricity demand were obtained from measurements of Liander, the largest utility company in the Netherlands, and have been used to generate unique profiles for each house. Profiles were allocated to each house according to the number of residents. Heat demand was also modelled as a non-controllable load. All heat demand has to be supplied immediately. The model does not differentiate between the quality of heat; heating heat demand (HHD) and domestic heat demand (DHD) are connected to the same energy pool (Fig. 2). Datasets for HHD and DHD were synthesized using a heating demand model [38,39] and a tap water model (Section 4.3), respectively. Unique profiles were generated for each house. Photovoltaic (PV) units were modelled as non-controllable generators. PV datasets were obtained from irradiation measurements of the Flemish Institute for Technological Research (VITO), and were used to create identical profiles for each house. Average annual figures are stated in Table 3.

4.3. Hot tap water submodel

DHD profiles for each house were determined by a hot tap water submodel, using statistics on household occupancy, diurnal patterns and water use.

Statistics on household occupancy for two-or-more-person households in 2050 were used to assign a number of residents to each household [40]. For each resident, we synthesised a unique consumption profile based on residential diurnal patterns of business travellers, adapted from Ref. [35]. Probability distribution functions of hot water use events (Fig. 3) were used to map random numbers to a stochastic variation in the start time of water use events. Any event is assumed to occur within the model's time step of 15 min.

Statistic data on the several end uses of hot tap water are given in Table 4. Average heat demand for hot water use events is 29 ± 2 Wh$_{th}$ per litre of tapped water, based on 100% penetration of waste water heat recovery in 2050 [34]. Using these statistics, the model synthesises unique DHD profiles for the entire duration of the simulation.

4.4. Predictions

Within the analysis method, control systems that manage Flex Street are required to use the same set of predictions for non-controllable demand and supply. We have created predictions with a forecast period of one day for each profile. The precision of predictions decreases for planning further into the future. This was modelled by moving the predicted demand $\tilde{P}$ away linearly from the realised values P for $0 \le t \le t_h$, according to [41]:

$$\tilde{P}(t) = P \cdot (1 - t/t_h) + \tilde{P}_h \cdot t / t_h \tag{1}$$

Here, the constant t_h amounts to 96 time steps (i.e. one day ahead) and $\tilde{P}_h$ is a set of predictions valid at the planning horizon of 96 time steps into the future. This dataset was generated in advance by imposing a stochastic variation on realised demand. The resulting prediction error for each dataset (Table 5) is based on an analysis of straightforward forecasting methods on the existing data (day-ahead forecasting and week-ahead forecasting). Currently, we have excluded predictions of domestic heat demand.

5. Case design

The rules of a control system comparison are defined in a case instance, which consists of a Flex Street scenario, a control system
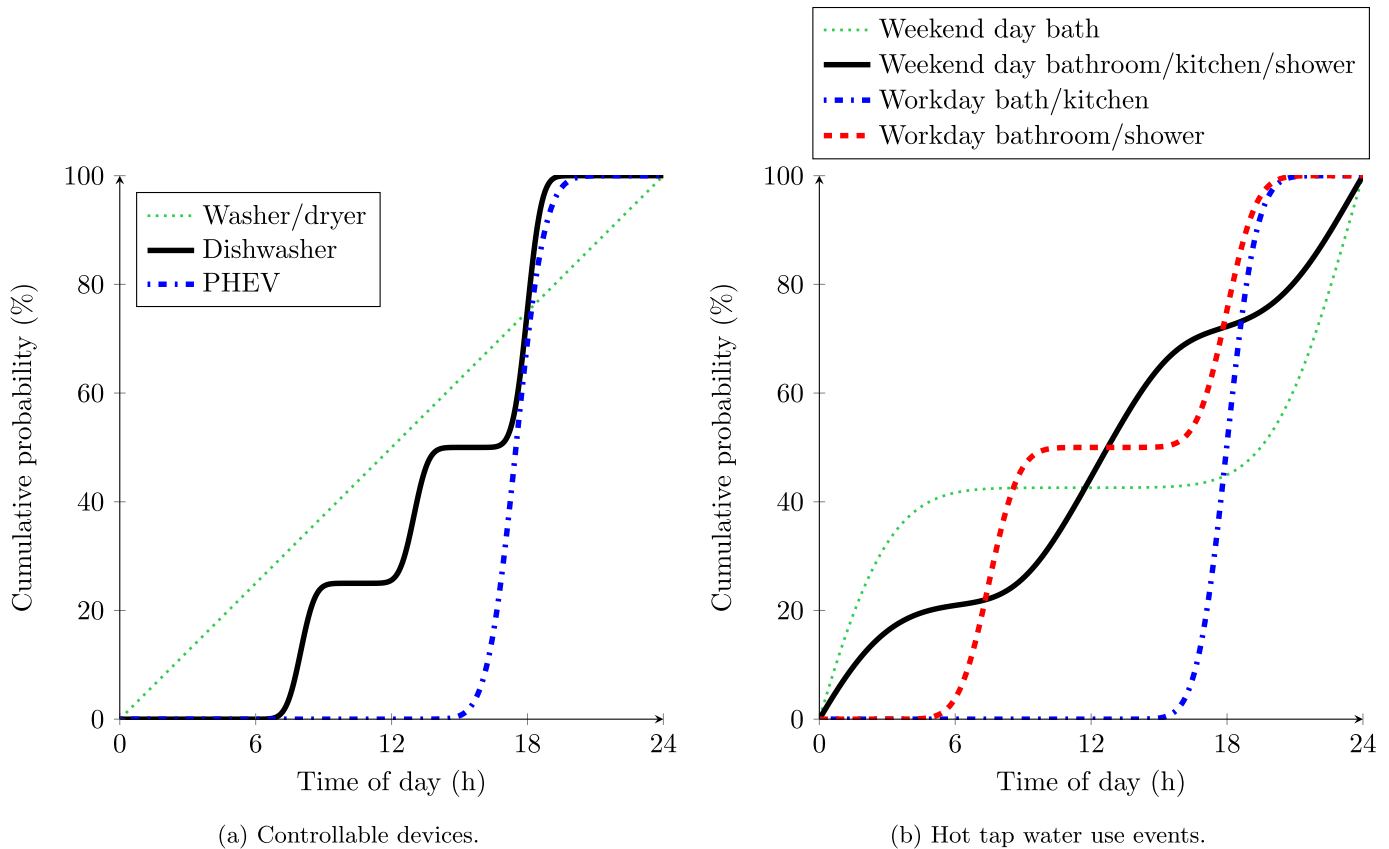
(a) Controllable devices.

(b) Hot tap water use events.

Fig. 3. Cumulative distribution functions describing start times of various devices and hot tap water use events.

objective and key performance indicators (KPI). To demonstrate our method, three exemplary cases were designed corresponding to the Flex Street scenarios in Table 1. The control objective and KPI are identical for each case.

Table 3
Average annual consumption/production per household for non-controllable loads and generators. Values represent a Dutch terraced house in 2050.

Type	Annual demand per household
Electricity demand	4.2 MWh
Heating heat demand	5.625 MWh$_{th}$
Domestic heat demand	1.875 MWh$_{th}$
PV	−4.4 MWh

Table 4
Statistics on end uses of hot water in the Netherlands based on several high-response surveys among Dutch residents, adapted from Ref. [35].

End-use type -subtype	Penetration rate (%/household)	Frequency[a] (person^{-1} day^{-1})	Water use per event (litre)	Heat demand[b] per event (Wh$_{th}$)
Bathtub	36	0.044	120	3493 ± 237
Bathroom tap				
- Washing and shaving	100	1	1.68	49 ± 3
Kitchen tap				
- Dishes and cleaning	100	1	6	175 ± 12
Shower	100	0.7	72.42	2108 ± 143

[a] The frequency for the kitchen tap is per household per day.
[b] Excluding standing losses and pipe losses.

5.1. Objective

A considerable amount of diversity is generated within the collection of houses in Flex Street, featuring different demand profiles of both non-controllable and controllable loads for each house. This set up is convenient when studying different control system objectives, as these can take into account the individual consumption patterns of households (for example, by rewarding a household for the amount of flexibility it has contributed to the microgrid).

Peak-shaving is the objective in all three exemplary cases. For an electricity supplier, minimising peaks in demand is a strong incentive to set up a microgrid. Supplying electricity at a more constant rate allows a retailer to buy from base load power plants instead of peak load power plants, which might lower the cost of electricity. Additionally, peak-shaving reduces the required capacity of the connection to the main grid, which can lead to investment savings.

Table 5
Mean Absolute Percentage Error (MAPE) for day-ahead predictions of demand during 15 min intervals. To avoid singularity problems for times with zero demand, the MAPE denominator has been defined as the average annual demand.

Type	MAPE (%)
Heating heat demand	18
Non-controllable loads	40
PV	46

5.2. Key performance indicators

KPI are defined to mark how well each control system has achieved the given objective. The following peak-shaving indicator was defined:

$$\text{Relative peak reduction} = \frac{\text{PP}_{\text{no control}} - \text{PP}_{\text{control}}}{\text{PP}_{\text{no control}} - \text{AP}} \qquad (2)$$

where PP is peak power and AP is average power.[2] The control systems were instructed to optimise for this indicator.

In order to evaluate the analysis method, several other indicators were used to demonstrate what information can be extracted from the simulation data.

Firstly, indicators were defined to measure savings and abated emissions due to a reduction of transport losses. The required spatial visualisation of transport has currently not been modelled in Flex Street; instead, a simple visualisation of the network has been assumed. Losses within the medium voltage (MV) distribution network have been calculated under the assumption that the microgrid is connected to a high voltage network by its own power line through the MV grid. Low voltage (LV) transport losses within the microgrid have been calculated assuming equidistant radial distribution. Line losses increase quadratically with power P, according to:

$$\text{Loss} = \frac{R}{V^2} \cdot P(t)^2 \cdot \Delta t \qquad (3)$$

$$\text{Annual transport costs} = \sum_t (B \cdot \text{Loss}) \qquad (4)$$

$$\text{Annual transport emissions} = \sum_t (E \cdot \text{Loss}) \qquad (5)$$

where:

KPI parameter	Value
B	0.25 €/kWh
E	67 g CO_2/kWh [a]
R_{LV}	292 mΩ [b]
R_{MV}	4.3 Ω [c]
V_{LV}	230 V
V_{MV}	10 kV
Δt	15 min

[a] Average global emission factor of grid electricity in 2050 from the BLUE Map scenario of the International Energy Agency [42]. The emission factor differs strongly in various scenarios for 2050 (from 19 to 341 g CO_2/kWh for OECD countries), depending on what new energy and climate policies are introduced by governments.
[b] A 400 m aluminium cable with 50 mm^2 cross-section is assumed [43].
[c] A 10 km Paper Insulated Lead Covered (PILC) copper cable with 50 mm^2 cross-section is assumed [43].

Secondly, indicators were defined to determine the seasonal performance factor (SPF) of heating systems and daily battery usage (DBU), both of which are unitless. The SPF is the average conversion efficiency of power P to heat H over the entire year:

$$\text{SPF} = \frac{\sum_t H(t) \cdot \Delta t}{\sum_t P(t) \cdot \Delta t} \qquad (6)$$

The maximum SPF is equal to the coefficient of performance (COP) of the heat pump. DBU is the average amount of power P flowing through the battery each day, relative to the battery's capacity C:

$$\text{DBU} = \frac{\sum_t P(t) \cdot \Delta t}{(1 - \eta) \cdot 365 \text{ days} \cdot C} \qquad (7)$$

where η is the efficiency of the battery. A battery with DBU = 200% would, for example, have two round-trips per day, on average.

Thirdly, indicators were defined to estimate investment savings in the LV network, including abated costs for upgrading transformer capacity, cables and ditches. We modelled these costs as a function of peak power PP, which corresponds to the neighbourhood's design value, i.e. the maximum average power flow in kVA per house, based on Ref. [44]. Costs of transformers, cables and ditches generally increase non-linearly with the design value, and are typically described by jump functions that represent the discrete increase of costs due to adding components and rearranging the network. For a growing number of households and new areas (e.g. for a complete region or country), such jumps level out and investment costs can be appropriately described by a smooth function. For a relatively small amount of households—such as in the present study—this model can only provide a rough estimate. To model the effect of marginal cost decrease, we used a power law for each component, with coefficients based on data from Refs. [44] and [45]. The investment costs are calculated as follows:

$$\begin{aligned} \text{Costs}_{\text{transformer}} &= 1.36 \cdot (\text{PP})^{0.50} \\ \text{Costs}_{\text{cables}} &= 2.96 \cdot (\text{PP})^{0.67} \\ \text{Costs}_{\text{ditches}} &= 616 \cdot (\text{PP})^{0.10} \end{aligned} \qquad (8)$$

with costs in euro per household and peak power in kW. In our results, we present the investment savings per annum, assuming an industry standard discount rate of 6% and an equipment lifetime of 40 years [46].

Together, these indicators demonstrate the method's ability of comparing smart grid control systems on their economic and environmental performance as well as on energy efficiency.

6. Simulations

The final step of the analysis method consists of simulations of different control systems for smart grids. The control systems manage the energy streams defined in Flex Street (Section 4), using the objective and KPI defined in the case (Section 5). To demonstrate the method, the IntelliGator and TRIANA control systems were compared.

6.1. IntelliGator

IntelliGator is a control system based on the PowerMatcher concept [47]. It is currently being developed independently at the Flemish Institute for Technological Research (VITO). The system is designed for real-time control. Prediction and planning are presently not part of the system's capabilities, but VITO is considering their implementation.

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[2] Peak power is defined as the load capacity covering the microgrid's load for 99.73% of the time. This corresponds to a coverage of 3 standard deviations from the average power if the load distribution would have been a normal distribution.

IntelliGator uses a multi-agent market with a hierarchical communication structure. Bids on electricity by device agents are sent to a central auctioneer agent. A Walrasian auction then determines a price that clears the market.[3] This equilibrium price is sent back to all local device agents, i.e. uniform pricing. It is a steering signal that informs devices how to dispatch themselves.

During real-time control, device agents generate bidding functions that define the allowed state transitions in the next time step. A business agent, representing the business objective of the network, generates a bidding function that also describes the network connection to the main grid as a device. The maximum power that the business agent can deliver depends on the capacity of the transformer connecting the network to the main grid. It is possible to create a steered market by letting the business agent adjust its bids in real time, influencing the market equilibrium and steering consumption towards some optimisation objective. For the Flex Street simulations, the business agent did not optimise in real time. Instead, it used the first 10 days of simulated data to optimise its bidding function for a peak-shaving objective, after which the bidding function remained fixed.

6.2. TRIANA

TRIANA is a control system developed at the University of Twente [41,48]. It is based on a three-step methodology of prediction, planning and real-time control. The system works in discrete time, performing real-time control steps during every time interval. Predicting demand and planning accordingly are steps that are repeated periodically, for a certain time horizon. TRIANA's prediction algorithm has been omitted in the present study, since its focus lies on the merit of the control architecture rather than on the accuracy of predictions. Demand predictions were constructed separately as part of the Flex Street model.

TRIANA uses a hierarchical system in which optimisation steps are performed on both local and central levels. A central controller optimises the planning towards a global objective. The system may send distinct steering signals (disguised as electricity costs) to local house controllers, i.e. non-uniform pricing. House controllers then execute a local cost minimisation, which results in a dispatch schedule for devices.

Planning steps begin with the configuration of a planning objective by drawing up a consumption plan. To induce peak-shaving, the consumption plan is set to a constant value, equal to the estimated total average consumption of the loads. Upon configuration, a planning is made through Iterative Dynamic Programming, executing central and local optimisation steps. In the simulations of Flex Street, a planning has been made every 6 h with a planning horizon of about 14 h.

During real-time control, local optimisation is performed at every time step, using integer linear programming. To save execution time in this study, Model Predictive Control was not incorporated in the implementation of the control system. Instead, the control system was instructed to reserve some scheduling freedom by planning devices to start a half hour later and finish a half hour sooner than predictions indicated.

6.3. Results

Our analysis method made it possible to use the existing simulators of VITO and the University of Twente. Subsequently, simulation results were obtained that enabled a straightforward comparison of the control systems for each of the Reference, Pessimistic, Moderate and Optimistic scenarios. This section presents the simulation output and a synopsis of the final results for all four scenarios; intermediate results are shown only for the Moderate scenario.

Fig. 4 presents a deconstruction of the aggregate demand of all houses in the microgrid during two days in winter. Fig. 4a, d and g show the demand without control for each scenario. Supply from PV units shifts the baseline to negative values around noon. Demand of non-controllable loads is shown directly on top of the baseline, followed by the electricity demand of heating systems (due to both heating and domestic heat demand), controllable appliances and electric vehicles. The number of houses equipped with a certain device depends on the penetration rate of the device (Table 1). In the Pessimistic scenario, none of the houses have electric heating systems. Batteries are available in 1/3 and 2/3 of the houses with PV installations in the Moderate and Optimistic scenario, respectively. Without control they are not used.

Heat demand during week days occurs primarily during mornings and evenings, while additional HHD occurs on weekend afternoons. Without control, the electricity demand of heating systems directly follows total heat demand. Fluctuating DHD results in jagged demand peaks. Controllable appliances are reasonably spread over the day. Electric vehicles are charged immediately after being plugged in, which causes an increase of peak demand during evenings.

Fig. 4b, e, h and c, f, i show the deconstruction again for when controlled by IntelliGator or TRIANA. The batteries are now able to reallocate part of the demand/supply from non-controllable loads/PV units. Batteries are discharging whenever demand is indicated below the baseline of PV supply. Sudden changes in battery behaviour at midnight, 6am, noon and 6pm result from TRIANA's replanning.

The figures demonstrate that electricity demand of controllable devices is distributed differently by the two systems. IntelliGator moves most peak demand to the early night, whereas TRIANA spreads demand more evenly over the night, by using the predicted duration of off-peak hours. Predictions are also used to fill up thermal storages prior to peaks in total heat demand. In the Moderate scenario, for example, TRIANA fills up storages during the predicted drop in demand, caused by solar irradiation around noon.

The annual load duration curve of the microgrid is presented in Fig. 5 for the Moderate scenario with and without control. The curve shows for what percentage of time the microgrid's load is higher than a given value of peak load. For example, point M marks the required capacity to cover the (uncontrolled) microgrid's load for 99.7% of the time (i.e. 1 day per year not covered).

To get rid of edge effects, the first and last 2 days of the year were masked in the analysis.[4] A plateau can be observed in the load duration curve of TRIANA, which shows that TRIANA is good at levelling off-peak demand. At the left side of the curve, the largest demand peaks have been decreased by both control systems: the relative peak reduction is 60% for IntelliGator and 63% for TRIANA.

The rest of the results demonstrate our method's ability to compare control systems for other performance indicators; in the present case study, the control systems were not optimised to take these indicators into account.

The objective of peak-shaving the aggregate demand of the microgrid reduces the peak capacity requirements of the medium

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[3] The terminology of IntelliGator uses 'priority' instead of 'price' or 'costs' to indicate that this quantity is decoupled from real monetary value.

[4] Edge effects occur for a number of reasons. For the first day, control systems cannot make a planning in advance, or control the initial state of charge for storage devices. For the last day, devices could be shifted to the next year, where they are no longer observed by the annual performance indicators.
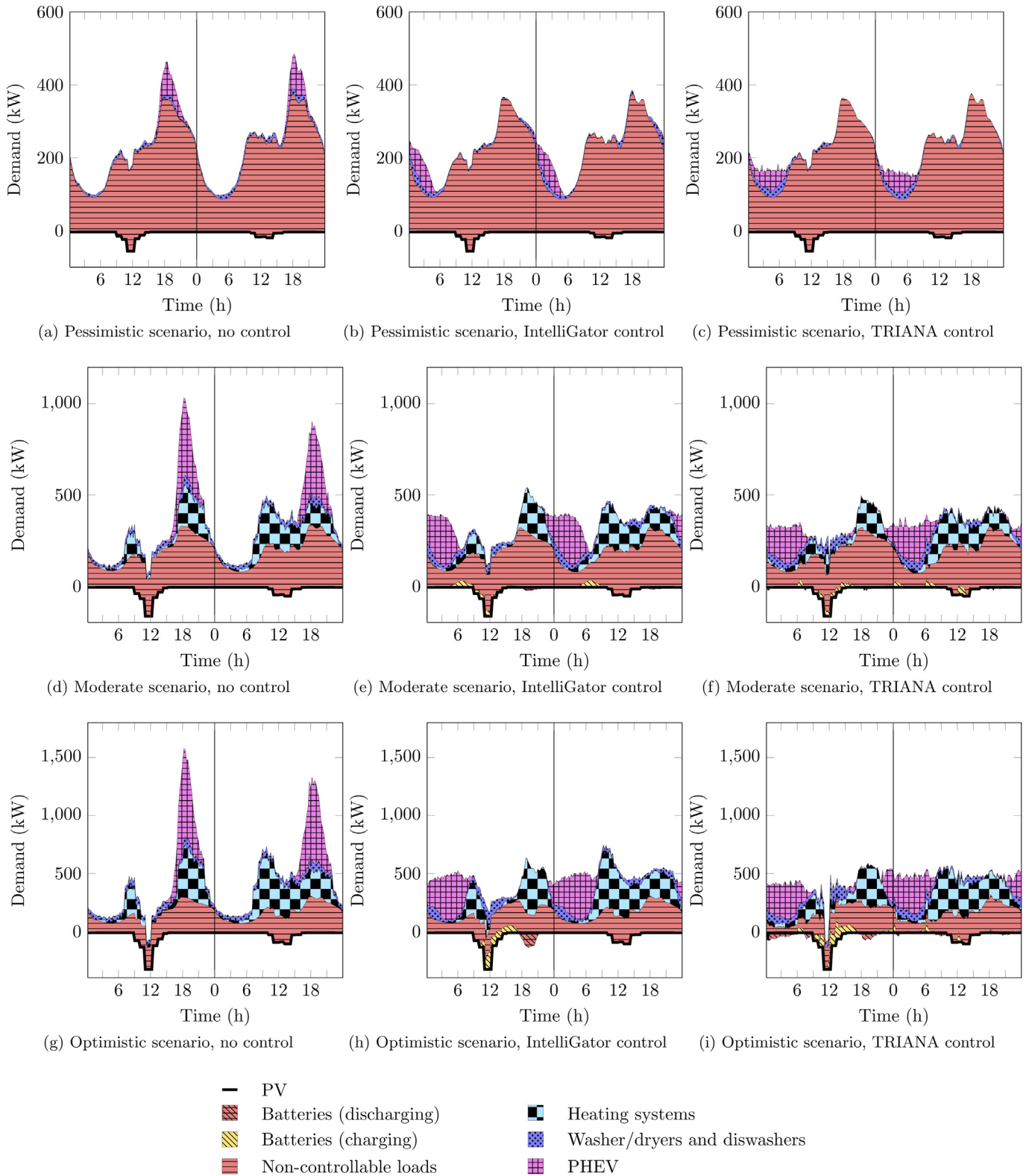
Fig. 4. Deconstruction of the microgrid's electricity demand into the individual contributions of the modelled devices. Days shown are a Friday and Saturday during winter. From left to right: without control and with IntelliGator and TRIANA control. From top to bottom: scenarios with pessimistic, moderate and optimistic penetration rates of controllable and renewable devices. The baseline indicates PV supply; any area underneath it indicates discharging batteries.

voltage (MV) network. Peak-shaving also helps in reducing MV transport losses, due to the quadratic nature of these losses. Table 6 shows annual transport costs due to line losses in both the MV and LV networks. TRIANA performed better in reducing MV transport

losses. Interestingly, IntelliGator reduced LV transport losses the best. Annual savings on reduced LV losses are shown per household in Fig. 6. IntelliGator accrued higher LV savings for individual houses with a large amount of controllability. To better reduce the
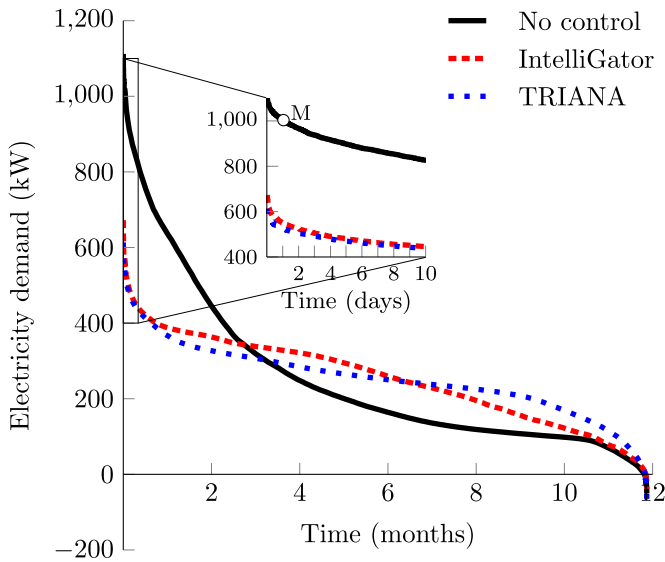
Fig. 5. Load duration curves of the microgrid in the Moderate scenario for no control, IntelliGator control and TRIANA control. The magnified section shows the duration of the largest demand peaks during the year.
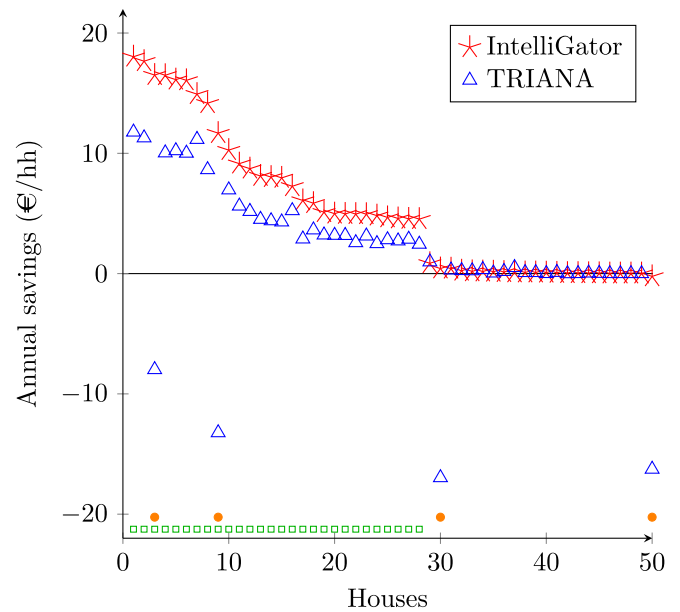

Fig. 6. Annual savings per household due to reduced transport losses in the LV network for IntelliGator and TRIANA. Houses with an electric vehicle are marked by a green square, houses with a battery installation are marked by an orange disk. 50 out of 400 houses are shown for the Moderate scenario, sorted by annual savings of IntelliGator.

MV transport losses outside of a microgrid, it appears worthwhile to increase internal LV transport. TRIANA has increased LV transport losses for houses with battery installations. This results from sub-optimal battery planning when supply exceeds demand in a house, causing oscillating battery behaviour around PV production hours.

Table 7 shows a synopsis of the demonstrated performance indicators for all scenarios. Printed in boldface is the peak-shaving indicator that the control systems optimised for. TRIANA achieved a slightly higher peak reduction (1–6%). The seasonal performance factors reveal that TRIANA made the most use of available heat pumps. The control systems show a significant difference in daily battery usage, but only a marginal difference in savings and abated emissions due to a reduction of transport losses.

Finally, the Flex Street analysis results can be used to help assess implications of smart grid control. Fig. 7 shows the impact of (IntelliGator) control on the annual investment costs in the LV network (Eq. (8)) for the 4 scenarios. Without a control system the capacity of the network needs to be increased with respect to the Reference scenario, resulting in extra investment costs for transformers, cables and ditches. Smart grid control tempers the necessary increase of investment by 64% in the Optimistic scenario and even leads to investment savings in the Pessimistic scenario, when a 4% reduction in required investment is obtained with respect to the Reference scenario. Investment savings are €3.55/household (Pessimistic), €12.57/household (Moderate) and €18.84/household (Optimistic), mainly due to avoided cables and ditches. Total annual savings due to network investments and transport losses in the distribution network, which are initially

Table 6
Annual transport costs per average household for line losses in the medium voltage (MV) and low voltage (LV) networks in the Moderate scenario.

System	Annual transport costs (€/household)	
	Due to MV losses	Due to LV losses
No control	25.84	21.13
IntelliGator	18.28	15.37
TRIANA	17.29	18.15

received by network operators and electricity suppliers, respectively, range from €5−54 per household.

7. Discussion

Our analysis method is designed to compare simulations of control systems, which are cheap and fast. However, a comparison of implemented control systems would be able to address other operational aspects, such as the running time of computations and the bit rate of communication. Even so, the current method can be improved by strengthening the Flex Street model in at least two ways.

Firstly, Flex Street uses bottom-up modelling of residential demand profiles. The effort of initially modelling many components is rewarded by creating a flexible tool for the analysis of smart grid control systems. Based on known or assumed characteristics of residents and devices, it easily allows constructing different profiles for houses. The ability to adjust such specific design parameters facilitates the design of new standardised cases.

Top-down datasets generally convey very little information on their composition, which hinders design revisions. Generating new cases is more convenient when a bottom-up approach is used in the entire model. Flex Street currently uses just two top-down datasets, i.e. for non-controllable electricity demand and solar irradiation.

Secondly, additional constraints can easily be added to Flex Street. Since transport losses in the LV network are in the same range as those in the MV network (Table 6), these should be clearly defined in the model in order to allow control systems to take these losses into account. Moreover, the specific network topology and local characteristics can be included in the model to obtain meaningful results for specific cases. Constraints limiting the power on internal lines, or LV transport costs, can then be incorporated in the objective function of a control system. Next to line losses, peak demand on LV lines should be considered an important parameter, determining investment costs more accurately.

Table 7
Summary of available performance indicators for the control system comparison. Annual savings and abated emissions are given per household to convey the results in a comprehensible unit.

Scenario	System	Relative peak reduction (%)	Seasonal performance factor (SPF)	Daily battery usage (DBU) (%)	Annual savings on transport costs (€/hh)		Annual abated transport emissions[a] (kg CO₂/household)	
					LV	MV	LV	MV
Pessimistic	No control	**0**	–	–	0	0	0	0
	IntelliGator	**32.1**	–	–	0.97	0.94	0.26	0.25
	TRIANA	**32.3**	–	–	0.94	1.15	0.25	0.31
Moderate	No control	**0**	4.25	0	0	0	0	0
	IntelliGator	**60.2**	4.83	23	5.76	7.56	1.54	2.03
	TRIANA	**63.3**	4.99	105	2.98	8.65	0.80	2.32
Optimistic	No control	**0**	4.28	0	0	0	0	0
	IntelliGator	**66.5**	4.83	44	12.57	22.54	3.37	6.04
	TRIANA	**70.6**	4.98	107	2.58	22.51	0.69	6.03

[a] The annual abated emissions depend on the emission factor from the associated IEA scenario. They can be 3.5 times smaller to 5 times higher.

Finally, a number of factors have not been incorporated in the model, that would be necessary for a full analysis of costs and benefits. On the one hand, these include investment costs of the required ICT infrastructure and operating costs due to e.g. the increased wear of batteries. On the other hand, additional benefits may result from trading electricity or ancillary services on the electricity market, from displaced peak load power plants, and from reduced network investments in the transmission network. The margins from the savings presented in this paper are such that the above factors need to be included in an analysis of costs and benefits for specific cases.

8. Conclusions

A comparison of the IntelliGator and TRIANA control systems demonstrates that our analysis method is able to quantitatively compare control system performance. Using the Flex Street model, three related cases were designed, depicting a microgrid with various penetration rates of controllable and renewable devices. In each case, the control system objective is peak-shaving the aggregate electricity demand of the microgrid over a one year period.
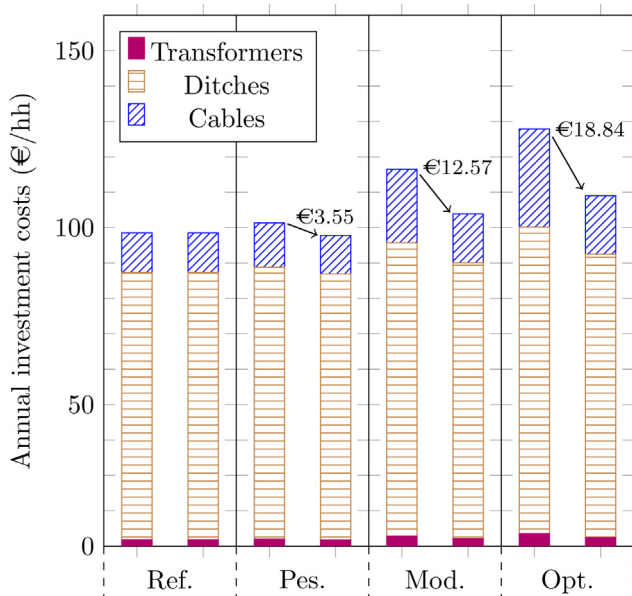

Fig. 7. Deconstruction of the annual investment costs of the microgrid without control (left) and with control (right) for the Reference, Pessimistic, Moderate and Optimistic scenarios.

Results show that performance differences are relatively small for this objective.

IntelliGator has been able to generate a relative peak reduction of 32–67% over the year, depending on the amount of controllability offered by the device population in each scenario. TRIANA has achieved a peak reduction of 32–71%. Savings and abated emissions due to the reduction in transport losses in the medium voltage network are similar for both systems. Savings occurred of 1–23 €/year per household and abated emissions were 0.25–6 kg CO₂/year per household.

In the simulations discussed here, the control systems had not been optimised to take into account transport losses in the low voltage network. However, our analysis shows that such losses may be significant and, therefore, should be taken into account. This could be implemented either by adjusting model constraints, or as part of a control system's objective function.

The analysis results were also used to help assess implications of smart grid implementation. Scenarios for 2050—with various penetration rates of controllable and renewable devices—have shown that peak-shaving can lead to benefits through reduced transport losses and network investments in the distribution network, totalling €5–54 per household per year.

Mutual learning is a benefit of comparative analysis, which is demonstrated by ongoing research at VITO and the University of Twente. Current research on the IntelliGator system is oriented towards incorporating planning in its business agent function, which should further increase performance. A self-learning business agent, able to adapt to seasonal effects using reinforcement learning, has already been developed. The developers of TRIANA are researching strong and weak points of auction-based real-time control, comparing it to TRIANA's current real-time control strategy based on integer linear programming. The integration of new optimisation techniques and network constraint handling is already in progress.

The Flex Street model provides a flexible tool for comparative analysis of smart grid control systems. Our analysis method is able to compare simulations of independently developed control systems using standardised cases with a broad scope. Flex Street facilitates case studies resembling a realistic setting for the operation of smart grid control systems. However, the method does not address quantitative indicators for some of the properties of an implemented system, such as run times of algorithms and communication speeds.

Flex Street can be improved by adding constraints on power lines or device usage to increase the complexity of the control task. However, simplicity remains a good property. And finally, it is possible to cover the entire model through bottom-up modelling of consumption/production, which would further increase the flexibility of Flex Street as a tool for smart grid researchers.

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