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Demand response for real-time congestion management incorporating dynamic thermal overloading cost

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HIGHLIGHTS

- Determination of a dynamic thermal overloading cost.
- Design of a demand response methodology for real-time congestion management.
- Agent-based distributed intelligence to solve the congestions locally.
- Local flexibility market to procure flexibility in a multi-actor setting.

ABSTRACT

Capacity challenges are emerging in the low-voltage (LV) distribution networks due to the rapid proliferation of distributed energy resources (DERs) and increasing electrification of loads. The traditional approach of network reinforcement does not achieve the optimal solution due to the inherent uncertainties associated with the DERs. In this article, a methodology of real-time congestion management of MV/LV transformers is proposed. A detailed thermal model of the transformer is used in order to obtain the costs incurred by overloading. An agent-based scalable architecture is adopted to combine distributed with computational intelligence for the optimum procurement of flexibility. The efficiency of the proposed mechanism is investigated through network simulations for a representative Dutch LV network. Simulation results indicate that the methods can effectively alleviate network congestions, while maintaining the desired comfort levels of the prosumers.

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1. Introduction

Driven by an effective international climate policy [1,2], the electrical distribution networks worldwide have been hosting an increasing share of renewable energy resource (RES) based distributed generation (DG) and new forms of load consumption such as electric vehicles (EVs), heat pumps (HPs), or electrical heating ventilation and air-conditioning (HVAC) systems. Along with a greener energy mix, these Distributed Energy Resources (DERs) bring forth operational challenges including voltage violations or thermal overloading of network assets [3,4]. Consequently, distribution system operators (DSOs) require to enhance monitoring and control ability in the network and a shift towards Active Distribution Networks (ADNs) becomes imminent [5–7].

Congestions or thermal overloading occur when the power flow through a network asset (e.g., lines, cables, transformers) exceeds its transfer capability. Although the network assets are generally designed to withstand loads beyond a certain margin, continuous overloading results in degradation of the insulation of the distribution cables and transformer windings [8,9]. The traditional approach of reinforcing the network assets in such cases, not only necessitates a huge investment, but will also be deemed redundant as the peak loads tend to appear only for few hours in a year [3]. To circumvent the required investment, a number of direct and indirect control approaches have been studied to tackle congestion issues in the ADNs. While the direct approaches mitigate congestions by curtailment of load and local generation [10,11], or by influencing the voltage level at the secondary side of a smart MV/LV transformer [12,13], their indirect counterparts motivate individual prosumers with...
flexibility in the distribution network and enables the DSO to obtain flexibility from a local capacity market to relieve network congestions. A more direct approach of graceful degradation complements the market-based control to curtail active power demand when adequate flexibility is not available in the market.

However, for a market-based DR mechanism, a sound methodology for real-time congestion management is significant in order to transform the realized aging of the network assets to a corresponding monetary loss. Based on the recent developments, an integrated congestion management mechanism is proposed in [9] for the residential distribution network incorporating dynamic thermal overloading model of a distribution transformer. However, in reality, procurement of flexibility in real-time appears to be a more complex problem involving scenarios with multiple market entities in the same congested network area [26]. This work extends the market-based control proposed in [9] further, incorporating computational intelligence in a multi-agent setting. The method will take advantages of the scalable architecture of the agent-based DR technology and detailed thermal model of oil-immersed transformers. A detailed case-study, involving 229 households is presented to illustrate the impacts and expected results of the proposed mechanism. The main scientific contributions of the paper are as follows:

- Demand response methodology incorporating the overloading cost, calculated from the dynamic thermal model of the transformer.
- Application of agent-based distributed intelligence to solve the congestions locally.
- An appropriate local flexibility market to procure flexibility in a multi-agent setting.

The remainder of the paper is organized as follows: Section 2 presents the overview of the market-based control, Section 3 describes the thermal loading model of the transformer, the methodology of flexibility procurement is detailed in Section 4, while Section 5 provides the description of the test scenario and the assumptions adopted. Finally, simulation results are presented and analysed in Section 6, before summarizing and concluding with Section 7.

2. Market-based control in distribution network

2.1. Flexibility in distribution network operations

Due to the increasing availability of the flexible domestic appliances and small-scale generation technologies like rooftop solar PV, market-based control of the distribution network has been drawing an extensive attention of late [27–29]. Apart from introducing new market entities such as aggregators and energy service companies, this has principally paved the way for a more decentralized operation of the future power system.

Different types of flexibility arrangements have been discussed in the literature with varied scopes and aims ranging from balancing services [28,30–32] to network congestion management [33, 27,34]. In this regard, price-based and incentive-based DR programs have been widely studied to invoke demand flexibility available in the network. A number of locational marginal pricing (LMP) methods have also been proposed for solving congestions based on day-ahead electricity market price [27,35]. Recently, local flexibility markets have also been proposed in order to facilitate a convenient interaction among the aggregators providing flexibility and the network operators who need the flexibility for network operations [36].

In this research, we develop a mechanism for real-time procurement of flexibility for congestion alleviation in LV distribution networks considering the incurred cost due to congestion. A bottom-up approach is adopted for modelling the loads of the residential prosumers. An agent-based system architecture is chosen for
a seamless coordination among the involved entities. To this end, a local flexibility market has been designed to obtain the flexibility provided by the aggregators.

2.2. Agent-based distributed architecture

Multi-agent systems (MAS) based distributed intelligence has been widely regarded as a reliable and efficient tool for solving complicated problems [37,10]. Compared to more centralized mechanisms, such decentralized approaches necessitate less computational burden and make it well-suited for large-scale problems involving multiple entities with conflicting interests. The PowerMatcher platform represents an efficient MAS-based DR platform that allows individual prosumers to actively participate in the real-time energy value chain. In this platform, DERs are represented by software agents with primary objective being an optimal operation of respective devices. The coordination is performed in agent environment with internal control signals ($\lambda$) expressed in per unit values ranging from 0 to 1 [38,22,23].

In this work, a hierarchical system architecture is implemented, as illustrated in Fig. 1. Device agents (DAs) represent the appliances and DG units connected in the physical network. Each of the households is represented by a house agent (HA) that coordinates the domestic device agents and works as the interface between the household and the external entities. The aggregator agent is responsible for coordinating the households in its portfolio of prosumers and determining the real-time control signals. Network agents, such as transformer agent (TA) and feeder agents (FAs) monitor and control respective network components. A more detailed description of the system architecture can be found in [9,39].

A local flexibility service agent (LFSA) is deployed to facilitate the adequate flexibility for the network operator. The LFSA gathers flexibility offers from the aggregators and selects the best offers matching the requested flexibility of the network agents.

2.3. Coordination mechanism

The priority of the devices in each time step, $t$, is portrayed by the bid of the device, $d^t_a$ as a function of the control price signal, $\lambda$. The bid is expressed in terms of expected levels of power consumption/generation in the next time interval for the price signals. Each of the DA considers the properties of the devices (e.g. nominal power rating, buffer capacity), user defined set-points (e.g. desired inside temperature of the household) and external parameters (e.g. outdoor temperature, building characteristics) while constructing the bids. At each time step, the HA collects the device bids and combines them in a house bid, $d^t_h$ such that,

$$d^t_h = \sum_{k=1}^{N_h} d^t_{h,k}. \tag{1}$$

The house bids are sent to the contracted aggregators for the development of the aggregated bid, $d^t_{a}$.

$$d^t_{a} = \sum_{h=1}^{N_h} d^t_{h,k}. \tag{2}$$

For the scalability purposes, the Aggregator can classify their contracted prosumers in separate clusters. This can, for instance be based on their geographical locations, network topology, annual energy consumption, amount of installed DG capacity, etc. In this work, we assume that aggregator clusters are constructed based on the network topology, i.e. prosumers connected in the same LV feeder are grouped under one cluster. Eq. (2) can thus be formulated as,

$$d^t_{a} = \sum_{h=1}^{N_h} \sum_{f_{a}^{h} = 1}^{N_f^h} d^t_{h,k}. \tag{3}$$

The aggregator calculates the equilibrium point as the control signal, $\lambda^*$ by matching the local supply and demand in its clusters. Thus, the estimated active power demand of $a$th aggregator at time $t$, $P^t_a$ can be derived from the bid as,

$$P^t_a = d^t_a \left( \lambda^* \right). \tag{4}$$

In every time step, the aggregator agent determines the available flexibility offers in each of its feeder clusters, $F_{of}$ and estimated demand. The flexibility offers and estimated demand are sent to the LFSA and the TA respectively. From the estimated load of all the aggregators, the TA determines the expected load in the next time step. In addition, the TA is updated about the instantaneous feeder loading, $S_{f}$ by the FAs and calculates the total transformer load. Next, the TA calculates the expected loss of life and corresponding overloading cost based on the thermal model of the transformer. The expected overloading cost, $C_{OL}^{af}$ is sent to LFSA in order procure flexibility from the aggregators. The LFSA selects suitable flexibility offers from the available ones and subsequently informs the aggregators regarding the selected flexibility offers, $P_{af}^{opt}$. Finally, the aggregators calculate the required adjustment of control signal, $\Delta \lambda_{of}$ for relevant clusters and determine the final control signal for the next time period. The final control signal, $\lambda_{of}^{**}$ is then sent to the DAs via the HAs to govern individual devices at the prosumer connection points. The mechanism at each time step, $t$ is schematically summarized by the UML sequence diagram shown in Fig. 2. Next sections describe the methodologies of calculation of the overloading cost and flexibility procurement more in detail.

3. Thermal overloading of transformer

Overloading of the MV/LV transformer may occur due to increased loads at connection points, for instance – simultaneous charging of the large number of EVs or switching of domestic HPs.
Although thermal overloading affects the insulation life-time of the transformer windings, thermal dynamics involved in the loading allows the transformer to be overloaded for a certain duration of time. Therefore, the procurement of flexibility needs to be aligned with actual status and corresponding cost of overloading of the transformer.

3.1. Determination of the loss of life

In each time step, the estimated loads of the aggregators supplying at a certain congestion point are used to determine the total expected load of the transformer, $L'_t$.

$$L'_t = \sum_{i=1}^{N} P'_t$$

(5)

where $P'_t$ expresses the expected load of $i$th aggregator at time $t$. The expected load is converted to corresponding hottest spot temperature, $\theta^{HS}_t$ of the transformer. According to IEEE standard C57.91-2011, the hottest-spot temperature, which is the highest temperature of the winding at the operating condition, is the principal factor in determining the expected life of a transformer [40,41]. To determine this temperature, a ratio called the load multiplex, $K_t$ is calculated and then used to calculate the top oil temperature rise, $\Delta \theta^{TO}_t$ and hottest spot temperature rise, $\Delta \theta^{H}_t$, as:

$$K_t = \frac{L'_t}{S_{rated}}$$

(6)

$$\Delta \theta^{TO}_t = \Delta \theta^{TR} \left[ \frac{K_t^2 R + 1}{R + 1} \right]$$

(7)

$$\Delta \theta^{H}_t = \Delta \theta^{TR} K_t^2$$

(8)

where $S_{rated}$ denotes the rated load of the transformer, $R$, $\Delta \theta^{TR}$ and $\Delta \theta^{H}$ express the ratio of load loss to no-load loss, top oil temperature rise and hottest-spot temperature rise at the rated load respectively.

The resulting hottest-spot temperature at time, $t$ is calculated by considering the temperature rise for the load conditions and the ambient temperature, $\theta^{A}_t$. The ambient temperature is the temperature of the air in contact with the radiators or heat exchangers of the transformer and can be approximated by either taking the average daily temperature or the average maximum temperature of the month over several years [41].

$$\theta^{A}_t = \theta^{A} + \Delta \theta^{TO} + \Delta \theta^{H}_t.$$  

(9)

The ageing acceleration factor, $\Phi^{AA}_t$ indicates the ageing of the transformer insulation and is calculated on the basis of Arrhenius reaction rate theory [41].

$$\Phi^{AA}_t = \exp \left[ \frac{15000}{T_0} - \frac{15000}{T + 273} \right].$$

(10)

The degradation in the insulation of a transformer is realized when the minimum time of overloading is 30 min [40,42]. In this work, a discrete step size of 15 min is considered. Since insulation degradation is realized with an overloading duration of 30 min, the equivalent ageing factor, $\Phi^{ eq}_t$ is determined by taking the historical load of the same time duration. If $N$ is the number of time intervals in half an hour and $\Delta t$ is the length of each time interval, $\Phi^{ eq}_t$ can be represented as,

$$\Phi^{ eq}_t = \frac{\sum_{n=1}^{N} \Phi^{ AA}_n \Delta t_n}{\sum_{n=1}^{N} \Delta t_n}.$$  

(11)

Considering a discrete time step size of 15 min, $\Phi^{ eq}_t$ is calculated by,

$$\Phi^{ eq}_t = \frac{\Phi^{ AA}_t + \Phi^{ AA}_{t-1}}{2}.$$  

(12)

The per unit loss of life of the transformer, $T^{ eq}_l$ is then given by,

$$T^{ eq}_l = \frac{\Phi^{ eq}_t \Delta t}{T^{ eq}_l}.$$  

(13)

where $T^{ eq}_l$ denotes normal insulation life in hours. In this work, the normal insulation life is assumed to be 180,000 h or 20.55 years, which represents a well dried, oxygen-free distribution transformer [41].

3.2. Overloading cost

The total owning cost (TOC) method is adopted for calculating the ageing cost of the transformer. The TOC method is considered to be one of the most cost and resource efficient methods for the economic analysis of transformers [43,5]. TOC is calculated over the lifetime of a transformer and considers the operation and maintenance cost of the transformer along with the initial cost. Let $C_p$, $C_{NL}$ and $C_{IL}$ being the purchase cost, no-load loss cost and load loss cost respectively, the TOC of the transformer, $C_{TOC}$ is given by,

$$C_{TOC} = C_p + C_{NL} + C_{IL}.$$  

(14)

The ageing cost is determined by multiplying the per unit loss of life, $T^{ eq}_l$ with the TOC.

$$C^{ ageing} = T^{ eq}_l C_{TOC}. $$

(15)

Finally, as expressed in Eq. (16), the overloading cost, $C^{ OL}_l$ is calculated by the arithmetic difference between the instantaneous ageing cost, $C^{ ageing}_l$ and the ageing cost at rated load of the transformer, $C^{ ageing}_R$.

$$C^{ OL}_l = \begin{cases} C^{ ageing}_l - C^{ ageing}_R & \text{when } C^{ ageing}_l > C^{ ageing}_R \\ 0 & \text{otherwise}. \end{cases}$$  

(16)

4. Procurement of flexibility

Upon determining the overloading cost, the DSO requests flexibility from the aggregators in order to resolve the congestion. The task of flexibility procurement is carried out by the LFSAs that works as the interface between the network agents and the aggregators. The estimated overloading cost is taken as the basis of the calculation and adequate flexibility is procured from the available offers of the aggregators.
4.1 Available flexibility

4.1.1 Aggregated flexibility

The aggregated bid represents the preference of all the prosumers in the portfolio of an aggregator. Thus, the available flexibility of an aggregator at a given time can be determined from the aggregated bids of corresponding aggregators. Let \( \lambda_a^+ \) being the equilibrium price for \( a \)th aggregator, flexibility is determined by taking the respective shift in power for each step of price shift in the aggregated bid. Thus, the flex bid, \( d_{a,h}^\text{flex} \) is given by,

\[
d_{a,h}^\text{flex} = \begin{cases} 0 & \text{if } \delta \lambda_a \leq \lambda_a^+ \\ d_a^h - \delta d_a^h & \text{if } \lambda_a > \lambda_a^+ \end{cases}
\]

\[(17)\]

4.1.2 Flexibility at feeder clusters

Due to the radial topology of the LV networks, a feeder level clustering is advantageous for managing the flexibility. This is performed by grouping the households connected at the same feeder together. Thus, the resulting flex bid of \( f \)th feeder for \( a \)th aggregator is given by,

\[
d_{a,f}^\text{flex} = \sum_i d_{a,f,i}^\text{flex}
\]

\[(18)\]

where \( d_{a,f,i}^\text{flex} \) expresses the bid of available flexibility at each house.

The flex bid corresponds to the available shifts from current equilibrium and can therefore be used for network support. The shifts are termed as flex offers and are calculated for each of the feeder clusters. Thus, the flex offers from \( f \)th cluster of \( a \)th aggregator is given by,

\[
F_{af}^{i} = d_{a,f,i}^\text{flex} \quad \forall i = 1, 2, \ldots, N^F_{af}
\]

\[(19)\]

where \( N^F_{af} \) denotes the number of available shifts for \( f \)th feeder cluster of the \( a \)th aggregator.

4.2 Selection of flex offers

The LFSA is responsible for selecting suitable flex offers to alleviate the load of the transformer. The procured flexibility thus helps mitigating the costs incurred by the transformer overloading. In this regard, the cost of the procured flexibility plays a crucial role, as the DSO may choose to overload the transformer and bear monetary losses instead of procuring flexibility at a much higher price. Per unit price of the available flexibility may also vary significantly, since it depends on the viewpoints of individual aggregators and involves complex market dynamics. In this research, a simplified approach is adopted, where the per unit price of the flexibility is assumed to be equal to the day-ahead electricity market price, \( C_t^{DM} \).

The TA seeks to lower the imminent overloading cost and informs the LFSA about the required flexibility and the estimated overloading cost at expected load. From the perspective of the LFSA, the optimization problem becomes a maximization problem constrained by the cost of required flexibility. This can be mathematically formulated as:

\[
\min_{u_{af}, x_{af}} -C_t^{DM} \sum_{a=1}^{N_a} \sum_{f=1}^{N^F_{af}} u_{af} x_{af} |F_{af}^{i}| \Delta t
\]

\[(20)\]

subject to,

\[
u_{af} = \begin{cases} 0 & \text{when not selected} \\ 1 & \text{when selected} \end{cases}
\]

\[(21)\]

\[
x_{af} = \begin{cases} 0 & \text{when not selected} \\ 1 & \text{when selected} \end{cases}
\]

\[(22)\]

\[
\sum_{i=1}^{N^F_{af}} x_{af}^{i} \leq 1
\]

\[(23)\]

\[
\sum_{a=1}^{N_a} \sum_{f=1}^{N^F_{af}} \sum_{i=1}^{N^F_{af}} u_{af} x_{af}^{i} |F_{af}^{i}| \Delta t \leq |L^e_t| - S_{rated}
\]

\[(24)\]

\[
C_t^{DM} \sum_{a=1}^{N_a} \sum_{f=1}^{N^F_{af}} \sum_{i=1}^{N^F_{af}} u_{af} x_{af}^{i} |F_{af}^{i}| \Delta t \leq C_t^{DM}
\]

\[(25)\]

Eqs. (21)–(25) depicts the constraints of the optimization problem. Constraints shown in equations (21) and (22) are imposed to represent the bounds for the binary decision variables, \( u_{af} \) and \( x_{af} \), which select the feeder clusters and corresponding flex offers respectively. Constraint in Eq. (23) dictates that, multiple flex offers from a single cluster cannot be selected. Constraints described by (24) and (25) limits the procured flexibility and associated cost within the acceptable range of the TA.

Once the local market is cleared by the LFSA, the selected flex offers are communicated to the aggregators for necessary adjustment in the bid for respective clusters. The adjusted control price is determined by the index of the selected flex offer of the concerned cluster.

\[
\lambda_{af}^{+} = \lambda_a^+ + \delta \lambda, i x_{af} \quad \forall i = 1, 2, \ldots, N^F_{af}
\]

\[(26)\]

where, \( \delta \lambda \) indicates the discrete step size of \( \lambda \).

The optimization problem described in (20)–(25) consists of integer variables and can be solved by Mixed-Integer Programming (MIP) technique. The entire process can be schematically summarized as shown by the flowchart in Fig. 3.

5. Simulation setup

The proposed methodology is evaluated with a simulation case study in a residential Dutch LV network. The network consists of three feeders, namely Feeder A, Feeder B and Feeder C. Total number of households connected in the feeders are 95, 42 and 92 respectively. As shown in Fig. 4, a 500 kVA MV/LV transformer feeds the network from the MV bus. All of the feeders comprise of underground power cables. The network model is built in MATLAB environment using the open-source Power System Analysis Toolbox (PSAT) [44]. Typical network parameters are tabulated in Table 1.

<table>
<thead>
<tr>
<th>Property</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transformer rating</td>
<td>10.25 kV/0.4 kV, 500 kVA</td>
</tr>
<tr>
<td>Transformer full-load loss</td>
<td>4.6 kW</td>
</tr>
<tr>
<td>Transformer no-load loss</td>
<td>0.62 kW</td>
</tr>
<tr>
<td>Purchase cost of transformer</td>
<td>€6000</td>
</tr>
<tr>
<td>Length of Feeder A</td>
<td>792 m</td>
</tr>
<tr>
<td>Length of Feeder B</td>
<td>658 m</td>
</tr>
<tr>
<td>Length of Feeder C</td>
<td>350 m</td>
</tr>
</tbody>
</table>

| Table 1 |

Network properties.
The equilibrium price, $\lambda^*$, as calculated by the aggregators is expressed in discrete per unit values between 0 and 1 with an increment of 0.05.

Apart from uncontrollable base loads, each of the households in the network are equipped with freezers, solar PV and heating devices. In order to meet the heating demand, 90% of the households consist of heat pumps, while the rest meet the demand with $\mu$CHPs. The uncontrolled base loads can be represented as aggregated loads of residential consumers and modelled using normalized profiles [8]. Such normalized profiles are available for 400 Dutch households [45], which are used to obtain the actual base load profiles considering 3400 kWh as average annual energy demand per household in the Netherlands. Typical rated values of other devices and parameters are presented in Table 2. Outdoor temperature and solar irradiation data are obtained from Royal Dutch Meteorological Institute [46].

The optimization problem defined by (21)–(25) constitutes integer variables and is solved by the mixed integer linear programming solver of the MATLAB Optimization Toolbox [47].

6. Numerical results

Snapshots of the simulation results of the case study are first presented for two consecutive winter days in the Netherlands. Subsequently, the annual performance of the proposed approach is analysed in terms of the cost savings and reduction in congestion duration.
Fig. 5. Internal price signals of three aggregators for uncontrolled case.

Fig. 6. Transformer loading without congestion management.

local load leading to the price set at zero. In such a case, the DSO cannot increase the load in the cluster by further lowering the price.

An equilibrium point exists when the local load matches the generation in the cluster. In this case the DSO can shift the load in both directions, thus procuring the available flexibility by altering the price depending on the level of thermal overloading. For instance, flexibility is available from all of the aggregators between 12:00 and 14:00 h in both of the days. Thus, congestions during these hours can be resolved by appropriate adjustment of the internal price.

6.1. Price adjustment for congestion management

Upon detection of the thermal overloading, the LFSA optimizes the available flexibility of the aggregator clusters in order to source flexibility for resolving the congestion. Fig. 6 depicts the transformer loading when the control methodology is applied along with the uncontrolled case.

As shown in Fig. 6, the transformer is overloaded at 13:00 h and 18:30 h on the first day. We investigate the congestion occurring at 13:00 h more in detail. With an expected loading of 1.10 p.u., an overloading cost of €0.26 is would have been realized. As depicted in Fig. 7, in order to avoid this overloading cost, 8.5 kWh of flexibility is required. Available flexibility of the clusters at this time step and their price considering the instantaneous day-ahead electricity price are tabulated in Table 3. The flexibility offer of 7.98 kWh of feeder B and Aggregator A1 is selected as it best matches the objective and constraints described in Section 4.2. Thus, the load becomes lower in the next time step and the overloading cost is avoided. Similar situations occur in the evening of the first day and flexibility is procured to relieve the congestion.

Congestions are observed to occur again during the evening of the second day. However, no flexibility is procured by the LFSA at these time steps. This is due to the fact that, the magnitude of the overloading cost and required flexibility is rather low compared to the cost and magnitude of the flexibility offers. Procurement of flexibility at this time would have resulted a higher cost for the network operator.

Table 3
Available flexibility and associated cost at 13:00 h on the first day.

<table>
<thead>
<tr>
<th>Feeder</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>11.78 kWh</td>
<td>15.24 kWh</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(€0.33)</td>
<td>(€0.43)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>12.18 kWh</td>
<td>15.64 kWh</td>
<td>(€0.44)</td>
</tr>
<tr>
<td></td>
<td>(€0.34)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.23 kWh</td>
<td>7.55 kWh</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(€0.12)</td>
<td>(€0.21)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>7.98 kWh</td>
<td>9.23 kWh</td>
<td>(€0.26)</td>
</tr>
<tr>
<td></td>
<td>(€0.23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>11.48 kWh</td>
<td>12.31 kWh</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(€0.32)</td>
<td>(€0.35)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13.60 kWh</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(€0.38)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4
Results summary for the simulated two days.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Uncontrolled case</th>
<th>Controlled case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overloading cost (€)</td>
<td>2.58</td>
<td>1.62</td>
</tr>
<tr>
<td>Incentive paid (€)</td>
<td>–</td>
<td>0.77</td>
</tr>
<tr>
<td>Total cost (€)</td>
<td>2.58</td>
<td>2.39</td>
</tr>
<tr>
<td>Savings (%)</td>
<td>–</td>
<td>7.85</td>
</tr>
<tr>
<td>Congestion duration (h)</td>
<td>3.25</td>
<td>2.25</td>
</tr>
<tr>
<td>Reduction (%)</td>
<td>–</td>
<td>30.77</td>
</tr>
<tr>
<td>Supplied energy (MWh)</td>
<td>19.07</td>
<td>18.70</td>
</tr>
<tr>
<td>Reduction (%)</td>
<td>–</td>
<td>1.94</td>
</tr>
<tr>
<td>Total loss (MWh)</td>
<td>1.21</td>
<td>1.17</td>
</tr>
<tr>
<td>Loss reduction (%)</td>
<td>–</td>
<td>2.90</td>
</tr>
</tbody>
</table>

6.2. Overloading cost

The effect of the proposed method is tabulated in Table 4 in terms of a number of performance metrics. In case of the controlled case, the total cost is determined by taken both overloading cost and the paid incentives in account. Please note that, the paid incentives in exchange of procured flexibility has to be distributed by the aggregator. The settlement between the aggregators and the prosumers has been left out of the scope of the paper, since this is subject to the contractual agreement between the involved parties.

The overloading cost is observed to be largely mitigated, while the incentive accounts for a large share in the total cost. The total cost corresponds to a similar value of the overloading cost in the uncontrolled case, since the flexibility is procured when the day-ahead price was relatively higher. However, the duration of congestion is minimized, thanks to the adjustment of the local price.

It is important to note that, the proposed mechanism works on the basis of an active supply–demand matching algorithm, where each of the devices works within a defined set point of comfort levels. The preference of each device (and hence the prosumer/household) is reflected in the real-time bid. That is why the comfort levels of the prosumers is generally never violated, even if the supplied energy is reduced while managing the congestions.

6.3. Performance analysis

The proposed method has been evaluated for the half-yearly and annual performance in terms of a number of indicators as shown in Table 5. A significant cost savings and reduction in congestion duration is realized by the price adjustment in the controlled case. The cost savings is achieved due to the much lower day-ahead electricity price compared to the estimated overloading cost. In spring and summer, the duration of the days are far longer than winter, leading to an abundant yield in solar PV generation. Consequently, local prices (control signals) drop and the loads tend
Fig. 7. (a) Required and procured flexibility by the LFSA during the simulated two days, (b) overloading cost, cost of procured flexibility and the day-ahead price.

Fig. 8. Histogram of the probability of daily average temperatures—(a) inside temperature of the freezers, (b) household interior temperature.

Table 5
Simulation results for longer simulation time window.

<table>
<thead>
<tr>
<th>Time horizon</th>
<th>Indicators</th>
<th>Uncontrolled loading</th>
<th>Controlled loading</th>
<th>Reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 months</td>
<td>Overloading cost (€)</td>
<td>2553.27</td>
<td>30.88</td>
<td>98.79</td>
</tr>
<tr>
<td></td>
<td>Incentive (€)</td>
<td>0.00</td>
<td>52.30</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Total cost (€)</td>
<td>2553.27</td>
<td>83.18</td>
<td>96.74</td>
</tr>
<tr>
<td></td>
<td>Congestion duration (h)</td>
<td>30.50</td>
<td>7.75</td>
<td>74.59</td>
</tr>
<tr>
<td></td>
<td>Total loss (MWh)</td>
<td>108.98</td>
<td>105.09</td>
<td>3.57</td>
</tr>
<tr>
<td></td>
<td>Energy supplied (MWh)</td>
<td>1087.35</td>
<td>1016.16</td>
<td>655</td>
</tr>
<tr>
<td></td>
<td>Overloading cost (€)</td>
<td>6735.87</td>
<td>93.10</td>
<td>98.62</td>
</tr>
<tr>
<td></td>
<td>Incentive (€)</td>
<td>0.00</td>
<td>181.1</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Total cost (€)</td>
<td>6735.87</td>
<td>274.20</td>
<td>95.93</td>
</tr>
<tr>
<td></td>
<td>Congestion duration (h)</td>
<td>88</td>
<td>24</td>
<td>72.73</td>
</tr>
<tr>
<td></td>
<td>Total loss (MWh)</td>
<td>201.70</td>
<td>192.66</td>
<td>4.48</td>
</tr>
<tr>
<td></td>
<td>Energy supplied (MWh)</td>
<td>1998.99</td>
<td>1821.07</td>
<td>8.90</td>
</tr>
</tbody>
</table>

to operate at the same time. For instance, in winter with scarce local generation, HPs tend to operate at temperature levels close to their lower operating margin. However, in spring they mostly operate closer to the upper margin of desired temperature. This affirms the previously reported issues of congestions in relation to price-responsive loads and RES-based DG units [3]. This can eventually be handled with a smarter operation of the aggregators through a better scheduling of flexible demands.

Freezers and HPs being the available flexible loads in the households, the impact of the price adjustment will be reflected back on the consumption patterns of these loads. Fig. 8 shows the histogram of the probability of the daily average temperature for all three feeders. For the freezers, a higher average temperature
is observed in the controlled case, as the devices tend to operate relatively closer to their highest acceptable temperature setpoints. Similar situations occur for the HPs, as the average inside household temperature for the controlled case is slightly lower than the uncontrolled case. It is important to note that, the temperature setpoints in both cases have not been violated. Thus, the comfort levels of the prosumers have been well represented by the bid and have been considered for the price adjustment.

7. Conclusions

The focus of this work has been to propose a suitable mechanism for real-time congestion management in LV distribution networks. An agent-based system architecture has been adopted to solve the problems through distributed intelligence. The residential load profiles have been generated by a bottom-up approach involving dynamic control signals. A detailed thermal model of the transformer has been used to observe the impacts on the life time of the winding insulation in a LV network with a dominant share of DERs. Subsequently, the resulting ageing of the transformer has been translated into monetary cost and a decentralized algorithm incorporating a local flexibility market has been developed in order to alleviate the cost and payable incentives.

The proposed methodology has been investigated through simulation of 229 households. Significant savings in overloading cost and congestion duration have been achieved by exploiting the flexibility through the local flexibility market. Simulation results also demonstrate the bottlenecks of network operations with a large share of DG and price-responsive loads. A high local generation results in a lower price and ends up overflowing the transformer by a large margin due to the increased load. However, in such a case, there remains ample scope of shifting the loads and lowering the overloading cost.

The adopted methodology assumes a robust and reliable ICT backbone embedded in the ADN. Such a communication infrastructure will necessitate a considerably large investment. However, the cost of installing ADN needs to be incorporated in the planning horizon of the network operator beside alternative planning approaches.

The future research in this topic will be directed to improving the aggregator operations with a smarter scheduling operations. A suitable scheduling mechanism will provide a better insight of available flexibility and associated costs. In addition, direct load control methods, like graceful degradation can be integrated with the market-based method to manage congestions when direct flexibility cannot be procured from the prosumers.

References


