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Optimized Consumer-Centric Demand Response

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Abstract— **Demand side management has focused more on centralized control and heavily depends on continuous consumer interaction, often overlooking consumer thermal and visual comfort. Distribution grid management will necessitate the active involvement of new market actors (i.e. prosumers, aggregators, distribution system operators, retailers, etc.), so a holistic approach becomes critical to transform demand into an active element of electricity system management. This paper presents a consumer centric demand flexibility framework, which facilitates the automated, human-centric demand response, minimizes consumer interactions and accommodates various power system ancillary services.**

***Index Terms*—demand side management, consumer-centric control, visual comfort, thermal comfort.**

I. Introduction

Increasing electricity consumption, infrastructure aging, growing costs and the proliferation of distributed intermittent energy resources pose significant challenges on the electricity grid. In fact, intermittent, distributed energy generation sources connected to the Low Voltage (LV) grid alongside demand inelasticity may lead to grid imbalances [12]. Such sources are by nature dispersed across the grid, unpredictable in terms of generation and with limited controllability. This poses considerable challenges in grid management and often creates network stresses that demand costly capacity upgrades. To this end, Demand Side Management (DSM) – adjusting consumption - has become a promising solution [4]. Demand response (DR) can effectively contribute in various power system ancillary services like load following, peak-shaving, network congestion management, etc., delivering higher real-time value than traditional peak-load management. However, current DR practices are either based on highly centralized control with limited feedback from the consumer and/or heavily depend on continuous consumer interaction. This renders them unattractive for versatile real-time applications and capacity response to grid requirements. Utilizing DR for regulation service provision undoubtedly requires automated and real-time demand coordination in the form of intelligent DSM strategies.

Past studies have shown that controlling demand can be reliable and cost-effective by establishing mechanisms that make demand responsive to wholesale spot prices [11]. Residential, small to medium commercial and industrial consumers were shown to effectively reduce peak energy demand in response to time-varying prices [5]. However, [10] suggests that current energy market operations and pricing schemes might have only a limited effect on actual demand, especially in the residential sector. One of the main limitations of traditional demand models is their focus on average rather than real-time demand.

Therefore, it is imperative for DSM strategies – including demand flexibility and control – to account for real-time environmental and behavioural parameters that eventually define the profile of demand [9]. In support of this, [13] evaluates occupancy profiling as an important factor of energy demand variation, arguing that energy loads are predominantly determined by human presence and activities (e.g. travelling to work).

As [3] argues, effective DSM strategies should continuously consolidate consumer preferences and facilitate them using intelligent control campaigns [6]; e.g. model predictive control (MPC) approaches yield such control strategies. More often than not, a Mixed-Integer Linear/Non-Linear Programming (MILP or MINLP) optimization problem is formulated in order to minimize energy demand or cost while constraining indoor environmental conditions within a given set of comfort boundaries [6]. Matching the demand flexibility requested over a given time horizon while constraining thermal and visual comfort levels within the allowed boundaries, gives an insight of the set of permissible and comfortable control strategies at the building level [6]. Thus, enabling personalized energy services through

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intelligent control strategies that maintain comfortable indoor conditions is of primary importance in modern DSM.

This paper presents the design and evaluation of a consumer centric demand flexibility framework, including a preliminary assessment of the control optimization approach, as an application supporting the aggregator's business role. It is structured as follows: Chapter II discusses the integrated demand flexibility framework including data management, loads modelling and flexibility calculation. Chapter III describes the control optimization implementation. Chapter IV gives an overview of the lab environment setup. Chapter V presents the evaluation of the proposed framework and, last but not least, Chapter VI concludes this work and discusses future directions.

II. Integrated Demand Flexibility Profiling Framework

The work presented in this paper revolves around the premise that demand flexibility (viz. the amount by which demand can be adjusted) can be derived from consumer preference models that quantify consumer discomfort as a result of such adjustments. We present an integrated framework for *device modelling, forecasting and control* (Figure 1) based on *consumer preferences modelling*, that delivers optimal control strategies for flexibility requests for various power system ancillary services. To put this in perspective, consumer demand flexibility profiles rely on visual and thermal comfort boundaries as well as a discomfort utility function that indicates the degradation that demand deviations (i.e. flexibility) may incur to a consumer's comfort. Defining and quantifying in real-time the boundaries and cost of demand flexibility, can deliver critical information to an automated demand control and optimization strategy.

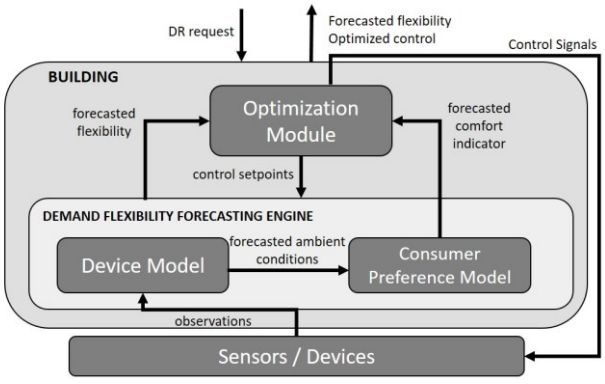


Figure 1 Overview of integrated demand response framework

In order to facilitate a consumer centric demand flexibility framework, Distributed Energy Resource (DER) modelling is required. They comprise the mathematical formulations for calculating electricity consumption of each DER type as a function of dynamic input data and static (configuration) parameters that affect DER operation. For example, the DER model for an HVAC system contains the mathematical model that calculates the power consumption of the HVAC given system and context characteristics (rated power, efficiency, building thermal properties) and dynamic operation inputs (temperature set-point, indoor/ outdoor temperature, etc.). In addition to energy consumption calculation, the enhanced DER models defined in this work further incorporate the impact that each DER operation has on indoor environmental conditions as an output parameter. With respect to DR capacity, the most favourable loads that provide demand flexibility are HVAC and lighting devices; hence, these are chosen for the remainder of this work.

Along with the definition of DER model parameters, the proposed framework aims to capture context awareness. Environmental conditions are associated with consumer actions, which are pivotal for the definition of visual and thermal comfort profiles, and consequently the flexibility profiling engine [9]. The aim is to define occupant temperature and luminance comfort boundaries that set the basis for extracting DER-specific flexibility values. Thermal and visual comfort profiles are based on the operation of controllable devices and the respective ambient conditions and provide an indication of the occupant's comfort level. To capture such correlations, Bayesian networks are selected as the probability density estimator underlying visual and thermal comfort profile models. The detailed framework for the extraction of occupant comfort profile models has been reported in [9]. The present work focuses on the presentation of enhanced DER models and their deployment to support an automated and personalized, integrated demand flexibility framework.

A. Data Management Layer – Nod Device

Data ingestion, logging and bi-directional communication with sensors and systems is needed for accurate DER modelling and consumer comfort profiling. The data management layer and its front-end, the NOD device, play this role. Data management is based on the concept of Service Oriented Architectures (SOA), using web services to communicate through standard protocols over a network. In this work, data management is facilitated through a set of representational state transfer (REST) services. The data management layer orchestrates messages across the components and appropriately transforms and routes the packages.

The NOD device (Figure 2) represents the system user-facing component towards appropriately understanding occupant behaviour in the built environment. Its purpose is to: i) gather information about perceived ambient conditions at individual spaces; and ii) collect user responses to these conditions (e.g. through control actions over lighting devices and HVAC loads). Therefore, NOD acts as a device tracking real-time context conditions and facilitating the

implementation of control actions. HVAC and lighting control signals are sent over Wi-Fi, through the data management layer to the respective device's REST Application Programming Interface (API).

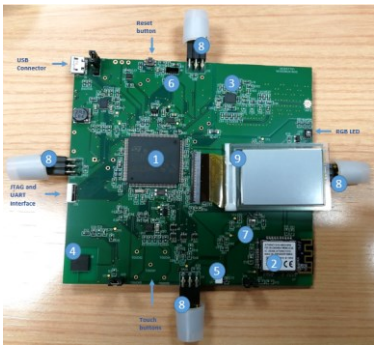


Figure 2 MOEEBIUS NOD

The following table describes the relevant sensors that the NOD device is equipped with for the present work:

TABLE 1 Sensor Types and Range

Type	Range	Accuracy
Temperature	-10ºC to +85ºC	+/- 0.4ºC
Humidity	0 – 100% RH	+/- 4%
Luminance	0.25 – 16 klux	+/- 10 lux

NOD sends sensor readings over Wi-Fi to the data management layer in one single packet. The data are sent every 5 minutes, an appropriate time granularity for accurate consumer comfort profiling and DER modelling.

B. Light Device Model

The light device model defines consumption as a function of status and dimming level. Therefore, learning the DER model for a light device is based on correlating consumption values with different device status and dimming levels. The following equation mathematically expresses a lighting device's consumption:

$$P^{output} = Nominal_P \cdot Status \cdot Dim_Level \quad (1)$$

Where P is the power consumption of the device (in W), Nominal_P is the nominal power of the device (in W), Status is a boolean (ON/OFF) and Dim_Level is the dimming level (%). The implementation considered in work is thoroughly described in [2] and is beyond the scope of this paper. [2] proposes a framework for the disaggregation of illuminance levels on ambient luminance and luminance contribution from lighting devices. Overall, the total impact is calculated as the linear impact of illuminance from lighting devices plus daylight illuminance. So, the enhanced DER model is defined by: a) a load profile as a function of dimming level and status; and b) the impact on illuminance level as a function of dimming level based on the process described in [2].

C. HVAC Device Model

With regards to HVAC system energy consumption, we are adopting the model proposed in [1][7][8] for modelling and controlling thermostatically controlled loads (TCL) for participation in DSM strategies. The considered HVAC device model correlates power demand with set-point, status (ON/OFF), ambient (outdoor) temperature and indoor temperature conditions.

The temperature evolution θ(t) of a thermostatically controlled load at cooling state, can be modelled according to [7] with a discrete time difference model:

$$\theta(t+1) = e^{-1/RC}\,\theta(t) + (1 - e^{-1/RC})\,(\theta_{amb} - PR) \quad (2)$$

Where θ_{amb} is the ambient (outdoor) temperature (in ºC), C is the thermal capacitance (in kWh/ºC), R is the thermal resistance (in ºC/kW), and P is the power demand of the TCL when ON. In steady state and during cooling periods, the HVAC drives a load from temperature θ_+ to temperature θ_-. The same approach is considered for heating where the power factor is set as -P.

Therefore, the final temperature calculation depends on input context conditions (indoor air temperature and ambient/outdoor air temperature) and configuration parameters (C, R, P and set-point) while the learning process consists of estimating C and R for each building zone examined using the least-squares regression approach.

D. Demand Flexibility Profiling Framework

The next step is the incorporation of comfort profiles to the DER modelling process in order to extract consumer centric demand flexibility profiles.

Comfort profiles are estimated based on the tolerance of users on ambient condition limits as well as inference of their preferred conditions stemming from control actions they make. A Bayesian network is used to establish the thermal/visual comfort profiles based on this information. More details can be found in [9].

More specifically, DER models output the resulting consumption and ambient conditions of given set-points/dimming levels while the comfort profiling engine defines the boundaries on ambient conditions. These are further incorporated towards enabling the accurate extraction of the potential of demand flexibility for each specific DER examined. In Algorithm 1, Setpoint is the operational point of each Device, Context is the impact of device operation on environmental conditions, VisualComfort and ThermalComfort is the comfort indicator based on the learnt consumer profile for visual and thermal comfort, respectively, and lastly Visual_Flex_Amount and Thermal_Flex_Amount is the amount of demand flexibility associated with the specific

set point operation and device. The overall analysis takes into account technical and operational constraints toward the evaluation of several control strategies. In fact, this algorithmic approach calculates the potential of controllability of each device type and makes this information available for exploitation in control strategies at building and district level.

The pseudo-code of the framework for the extraction of context aware demand flexibility profiles is shown in the following algorithm:

Algorithm 1 Demand Flexibility Calculation Pseudo-code

```
for i=1:Devices
    for j=1:Setpoint
      Actual_Consumption(j) = DER_Model( Device(i), Setpoint );
      Baseline_Consumption(j) = DER_Model( Device(i), Current_Setpoint);
      Context = DER_Model( Device(i), Setpoint );
      VisualComfort(j) = VisualComfort( Device(i), Context );
      ThermalComfort(j) = ThermalComfort( Device(i), Context );
      Visual_Flex_Amount(j) = Baseline_Consumption(j) – Actual_Consumption(j);
      Thermal_Flex_Amount(j) = Baseline_Consumption(j) – Actual_Consumption(j);
    end
end
```

By taking into account the respective flexibility amount and comfort value, we can select control strategies (Setpoints) considering business (Demand Response) and contextual (comfort constraints) objectives. In this paper, we consider the individual optimization of thermal and visual flexibility using the demand flexibility profiling framework described above. The approach of control optimization is briefly described in the next section.

III. Control Optimization

The aim of the current control implementation is to allow for demand flexibility provision while retaining comfortable ambient conditions for the consumer, in the vicinity of the NOD device. The goal is to control a set of devices that affect visual and thermal comfort in order to deliver a specific amount of demand flexibility. In this paper, two separate control optimizations are preformed; viz. one that offers maximum thermal flexibility and one that offers maximum visual flexibility.

The DER Models described above play a pivotal role in predicting the future behaviour of each device type and therefore they are useful for near-future control optimization. The formalization of the optimization approach used in this work is given below:

$$\begin{aligned} &\min J_k \\ &\text{s.t.} \\ &u_{min} \le u(k+j \mid k) \le u_{max} \qquad \forall\, j = 1, \ldots, N_u \\ &y_{min} \le \hat{y}(k+j \mid k) \le y_{max} \qquad \forall\, j = 1, \ldots, N_u \end{aligned} \tag{3}$$

Where, N_u is the future control horizon; $u(k+j \mid k)$ is the control signal at time $k+j$, computed at time k; u_{min} / u_{max} are the lower/ upper control boundaries of the device; y_{min}/ y_{max} are the lower/ upper comfort boundaries learnt for the user.

For simplicity, an objective function J is selected to represent the maximum amount of flexibility that can be offered at time j within the time horizon:

$$J_k = -\sum_{i}^{Devices} \sum_{j=1}^{N_u} Flexibility_{device}(u_{ij}) \tag{4}$$

We retain the minimization formulation in equation 3 and negate equation 4 to convert it to a maximization problem. Where i ∈ Devices and u is the control signal at time j. Note that $flexibility_{device}$ is calculated from Algorithm 1 for a given set-point. For simplicity and illustrative purposes, a greedy optimization approach is applied on a 2-hour horizon.

IV. Lab Environment Setup

A lab (controlled) environment is used for an initial evaluation, as depicted in Figure 3.

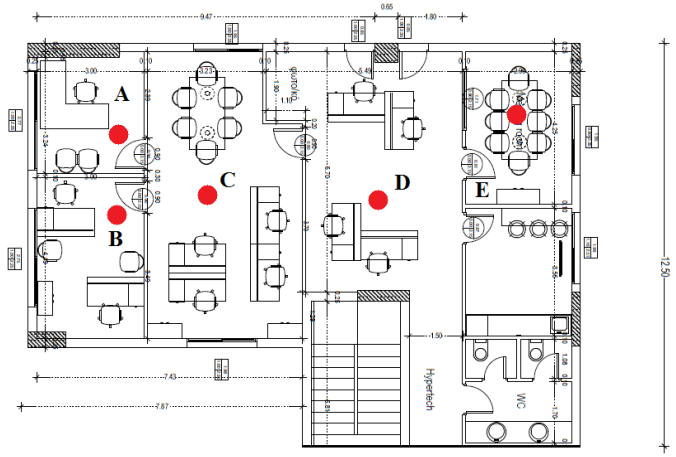


Figure 3 Lab Setup

This lab consists of the minimum infrastructure (loads as presented above, sensors, actuators, metering equipment and respective software) in a controlled environment to facilitate the smooth integration and operation of the heterogeneous system elements. Five zones are selected for experimentation (indicated by the red dots in Figure 3).

V. Demand Flexibility Evaluation

Initially, consumer visual and thermal comfort profiles are extracted considering real-time and historical contextual data per zone. Following a training process of one month, the thermal and visual profiles are obtained for all zones. The consumer profiling curves learnt for Zone C are visualised in Figure 4. This discomfort indicator and boundaries are useful as constraints for demand flexibility estimation, the aim of the current analysis. Note, that the optimal comfort point resides at the global minimum of the discomfort indicator. Discomfort boundaries are set at discomfort levels of at most 20% (i.e. comfort of 80% or above).

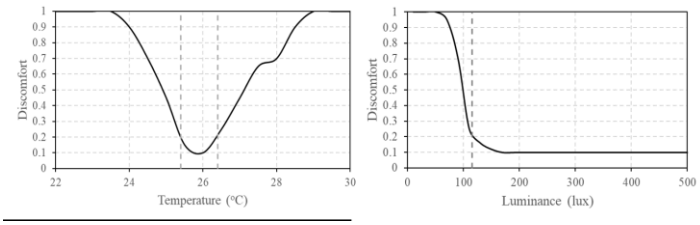


Figure 4 Thermal and Visual Profile

As also shown in Figure 4, thermal comfort profiling boundaries appear to define a tight dead-band around the optimal comfort value, which spans an average of 1.5ºC across all zones. This dead-band can limit the available demand flexibility potential of the HVAC system.

Alongside the consumer centric comfort profiling discussed above, DER models are extracted for each zone.

Figure 5 presents the load profile of an HVAC unit (Zone A), accompanied by the DER model characteristics as extracted during the learning process; including nominal power and duty cycle characteristics. The same analysis is provided for lighting device modelling. The nominal load profile and the impact on indoor illuminance are derived from time series analysis as depicted in Figure 6 for Zone C.

Finally, the evaluation of the maximum flexibility control strategy is carried out. The extraction of demand flexibility profiles is based on the DER models, incorporating as constraints the comfort profiles presented above and involve data that span one workday during summer (5/7/2017) between 13:30 and 15:30, for all zones considered.

Indicative results are depicted for Zone C on 5/7/2017 between 13:30 – 15:30 after the optimization process in Figure 7 and Figure 8, for HVAC and Light device, respectively.

For the selected time-period (13:30 to 15:30), the thermal flexibility potential (expressed in terms of potential load shedding) is 0.81% with comfort level around 90%.

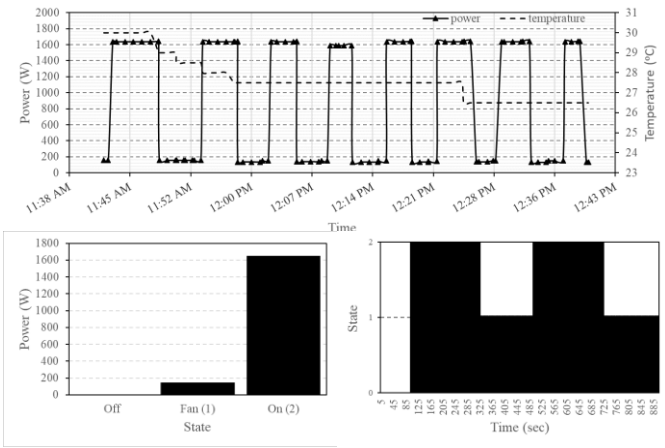


Figure 5 HVAC DER Model

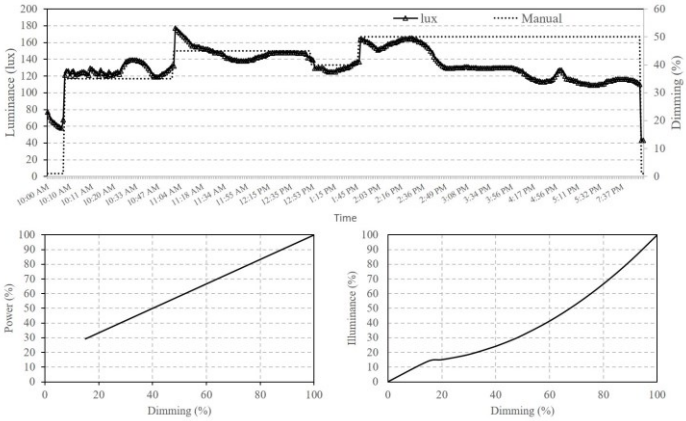


Figure 6 Light DER Model

Note that thermal load flexibility (shedding) is mainly restricted by the steep curvature of the thermal comfort profiling curve (Figure 4). Hence, lower comfort levels that are connected to higher flexibility values are constrained by human preferences.

The same analysis is performed for lighting devices, highlighting the relation between dimming level (%) and demand flexibility potential while preserving consumer preferences. Potential load shedding is approximately 40% with comfort level being around 85% as presented in Figure 8.

It is evident that lighting devices offer a higher demand flexibility in relative terms. This is due to the fact that consumers consistently keep the lights at higher dimming levels compared to their visual comfort boundary. Furthermore, visual profiling boundaries are one-sided compared to the two-sided thermal comfort boundaries.

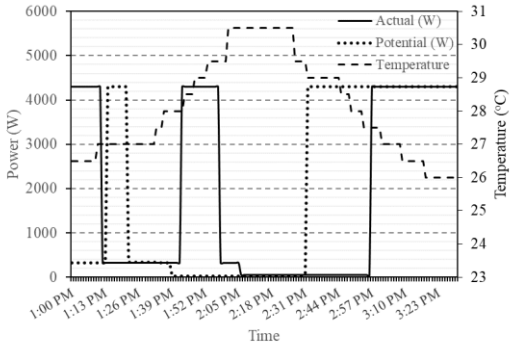


Figure 7 HVAC Device – Demand Flexibility Profile

TABLE 2 summarizes the results for the five zones that comprise the lab environment. The analysis shows a high potential of demand flexibility without compromising consumer comfort, enabling the establishment of a context aware demand side management framework under different business objectives.

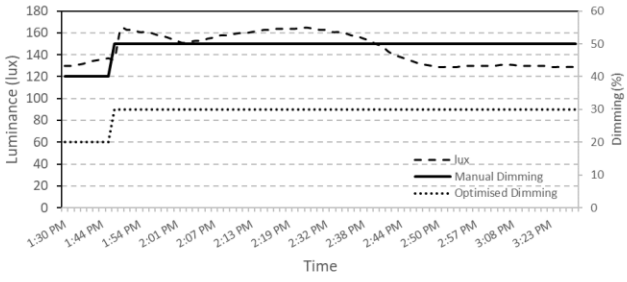


Figure 1 Light Device - Demand Flexibility Profile

With respect to thermal flexibility, Zone A shows a case where consumer thermal comfort has a less steep curvature, allowing for higher energy savings without significant comfort sacrifice. Zones C and D are the ones with the least thermal flexibility; this is associated with zone size and its direct relation to HVAC performance. On the other hand, Zones B and E, exhibit typical zone flexibility behaviour.

For visual flexibility, Zone B demonstrates the highest flexibility in sacrifice of comfort; this is related to higher ambient luminance. Zones A, C and D resemble a typical zone for visual flexibility with an average offered flexibility of around 40%.

VI. Conclusion And Future Work

This paper presents a novel framework for consumer centric automated control in residential and commercial buildings for demand side management applications. The framework comprises a context aware profiling mechanism that adapts to real-time events and ambient conditions, enhanced DER models that can forecast future device behaviour and a control optimization implementation to generate control commands for maximum demand flexibility. In this way we define an innovative context aware flexibility profiling framework that enables the implementation of more accurate and fine-grained control strategies as part of an automated mechanism.

Pilot studies indicate average shedding of around 7% for thermal loads and more than 30% for lighting while retaining comfort levels above 80% on average. As future research we consider the implementation of a combined visual and thermal control optimization approach to explore potential trade-offs between them for low, medium and high demand response signals. The thorough evaluation of the proposed framework in MOEEBIUS pilot sites is work in progress.

Acknowledgment

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TABLE 2 Demand Flexibility Potential – Summary

	Thermal		Visual	
	Shedding	**Comfort**	**Shedding**	**Comfort**
Zone A	14.22%	86.43%	43.10%	82.28%
Zone B	7.47%	94.74%	78.55%	80.02%
Zone C	0.81%	91.25%	40.21%	85.01%
Zone D	2.35%	92.35 %	35.38%	87.91%
Zone E	9.87%	93.96 %	33.35%	90.00%

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