This is an electronic reprint of the original article.
This reprint may differ from the original in pagination and typographic detail.

Bashir, Arslan Ahmad; Pourakbari-Kasmaei, Mahdi; Contreras, Javier; Lehtonen, Matti

A novel energy scheduling framework for reliable and economic operation of islanded and grid-connected microgrids

Published in:
Electric Power Systems Research

DOI:
[10.1016/j.epsr.2019.02.010](https://doi.org/10.1016/j.epsr.2019.02.010)

Published: 01/06/2019

Document Version
Peer reviewed version

Published under the following license:
CC BY-NC-ND

Please cite the original version:
Bashir, A. A., Pourakbari-Kasmaei, M., Contreras, J., & Lehtonen, M. (2019). A novel energy scheduling framework for reliable and economic operation of islanded and grid-connected microgrids. *Electric Power Systems Research*, 171, 85-96. <https://doi.org/10.1016/j.epsr.2019.02.010>

A Novel Energy Scheduling Framework for Reliable and Economic Operation of Islanded and Grid-Connected Microgrids

Arslan Ahmad Bashir^{1*}, Mahdi Pourakbari-Kasmaei¹, Javier Contreras², and Matti Lehtonen¹

¹ Department of Electrical Engineering and Automation, Aalto University, 02150, Espoo, Finland (e-mails: arslan.bashir@aalto.fi, mahdi.pourakbari@aalto.fi, matti.lehtonen@aalto.fi)

² E.T.S. de Ingenieros Industriales, University of Castilla–La Mancha, 13071 Ciudad Real, Spain (e-mail: javier.contreras@uclm.es)

* Corresponding Author

Abstract—This paper proposes a novel energy management framework by combining proactive and reactive approaches to efficiently address the uncertainties associated with generation and demand in islanded and interconnected operation of residential microgrid (MG). The MG considers renewable energy sources (RESs), a diesel generator (DG), and a storage device with the possibility of power exchanges with the grid. The proposed formulation is cast as stochastic mixed-integer linear programming (MILP) model with 24-hour rolling horizon, simulated periodically by updating input data and advancing on an hourly basis for a one year scheduling period. The objective is to minimize the total MG cost while preserving comfort priorities of individual households. The energy balance is potentiated by smart central management system of heating, ventilation and air-conditioning and electric water heater loads in conjunction with exploiting the building thermal inertia of well-insulated buildings. Random outages of MG components are modeled via a two-state Markov chain process, which is considered in the reactive approach. Extensive numerical results are presented to reveal the benefits obtained by coordinating the DR and supply sources for a practical case of Helsinki, Finland. Finally, the impact of various system parameters on the optimal expected MG cost and risk indices is investigated.

Index Terms—Uncertainty, mixed-integer, stochastic, Markov chain.

NOMENCLATURE

Sets

H	Set of hours $\{1, 2, \dots, 24\}$
M	Set of DG cost segments $\{1, 2, \dots, 9\}$
N	Set of households $\{1, 2, \dots, 50\}$
S	Set of scenarios $\{1, 2, \dots, 27\}$

Indices

h	Hour of the optimization horizon; $h \in H$
Δh	Difference between two consecutive time steps, i.e., one hour
m	DG segment $m \in M$
n	household $n \in N$
s	scenario $s \in S$

Variables and Functions

$b_{s,h}^{ch}, b_{s,h}^{dch}$	Binary charging / discharging decision of the battery energy storage (BESS) in hour h and scenario s
$b_{s,h}^{a,n}, b_{s,h}^{b,n}$	Binary variables for linearizing the absolute value function of household n in hour h and scenario s
$C(P_{s,h}^g)$	DG operating cost in hour h and scenario s (€)
$I_{s,h}$	Binary commitment status of the DG in hour h and scenario s
$LG_{s,h}, LL_{s,h}$	Total lost generation / lost load in hour h and scenario s (kWh)
$P_{s,h}^g$	Total production of the DG in hour h and scenario s (W)
$P_{s,h}^m$	Production level of the DG in segment m , hour h and scenario s (W)
$P_{s,h}^{ewh,n}$	Power consumption of the water heater of household n in hour h and scenario s (W)
$P_{s,h}^{b,ch}, P_{s,h}^{b,dch}$	Charging / discharging power of the BESS in hour h and scenario s (W)
$P_{s,h}^{export}, P_{s,h}^{import}$	Power sold / purchased to / from the distribution grid (W)
$Q_{s,h}^{hvac,n}$	Power consumption of HVAC unit of household n in hour h and scenario s (W)
$Q_{s,h}^{a,n}, Q_{s,h}^{b,n}$	Positive auxiliary variables for HVAC of household n in hour h and scenario s (W)
$SOC_{s,h}$	State of charge of BESS in hour h and scenario s (kWh)
$SU_{s,h}, SD_{s,h}$	Start-up / shut down cost of the DG in hour h and scenario s (€)
$T_{s,h}^{a,n}, T_{s,h}^{m,n}$	Indoor / building mass temperature of household n in hour h and scenario s (°C)
$T_{s,h}^{dhw,n}$	Hot water temperature of household n in hour h and scenario s (°C)
T_s^{LL}	Percentage of time when demand is higher than available supply in scenario s (°C)

Parameters

a	Fixed cost for running DG at its minimum output
c_w	Specific heat capacity of water (J/kg/K)
C^a, C^m	Indoor air heat capacity / Building fabric capacity (J/ °C)
D^{bess}	BESS degradation cost (€/kWh)
F_h^n	Fixed or critical load of household n in hour h (W)
$G_{s,h}$	Solar irradiance in hour h and scenario s
G_{ref}	Solar constant, i.e. 1000W/m ²
H^e	Heat conductance (W/°C) between external air and indoor air node points
H^g	Heat conductance (W/°C) between indoor air and ground node points
H^m	Heat conductance (W/°C) between indoor air and building mass node points
H^y	Heat conductance (W/°C) between external air and building mass node points
H^x	Heat conductance (W/°C) between HVAC air and indoor air node points
I_{sc}	Short circuit current of a PV cell
p_r	Rated output power of the WT generator (W)

$P_{s,h}^{PV}, P_{s,h}^{WT}$	Production level of the photovoltaic system / wind turbine in hour h and scenario s
$PV_{\max}$	Rated maximum yield of the PV system (W)
$P_{s,h}^{g,\min}, P_{s,h}^{g,\max}$	Minimum / maximum dispatch level of the DG (W)
$P_{s,h}^{ewh,\max,n}$	Rated maximum power of EWH unit of household n (W)
$Q^{\max,n}$	Rated maximum power of HVAC unit of household n (W)
S_I	Solar Insolation (W/m ²)
$T_{s,h}^e$	External temperature in hour h and scenario s (°C)
$T_{set}^{hvac}, T_{set}^{dhw}$	HVAC / DHW set point temperature (°C)
T_{in}	Temperature of in-let cold water in the hot water tank (°C)
T^x, T^g	HVAC ventilation air temperature / Ground node temperature (°C)
T_j	PV Cell temperature (°C)
V^{LL}, V^{LG}	Value of lost load / lost generation (€/kWh)
$V_{use,h}^n$	Volume of hot water used by household n in hour h (L)
V_{tank}^n	Volume of hot water tank of household n (L)
$w_{s,h}^w$	Wind speed in hour h and scenario s (m/s)
w_c, w_r	Cut-in speed / rated wind speed for the WT (m/s)
ρ_s	Probability of a scenario s
θ_h^n, ϕ_h^n	Thermal discomfort / hot water discomfort penalty factor of household n in hour h (€/°C/h)
λ_h^{DA}	Day-ahead price of electricity in hour h (€/kWh)
ψ	Fixed distribution tariff for importing power into the MG (€/kWh)
δ	Value added tax on day-ahead price expressed as a percentage of day-ahead price
ω	Fixed commission deducted by the distribution system operator (DSO)
η_c, η_d	Charging and discharging efficiency of the BESS
σ^n	Indoor air temperature dead band of household n (°C)

1. INTRODUCTION

The consistently rising concerns about the harmful environmental impacts of the fossil-based electricity generation, volatility and uncertainty in power prices, and continuous demand growth together, have resulted in increasing interest and deployment of high levels of renewable energy sources (RESs) around the world [1]. RESs mainly include solar, wind, biomass and tidal energy. Among the sustainable sources, solar and wind are easily available but they are highly intermittent and stochastic [2]. Hence, storage facilities and conventional sources as a backup plays a significant role in supporting the system operation. The integration and control of such components along with controllable and fixed loads at the low-voltage level form a network, a microgrid (MG), that can be operated either in islanded or grid-connected mode [3].

The concept of MG is naturally tailored to unite RESs which compensate for the cost of conventional generation. Moreover, the current energy policies at the EU level, e.g., Paris Climate Agreement, urge to shift to 100% green energy infrastructure. However, the integration of RESs to the power system is challenging due to their inherent intermittency and volatility. The forecasting errors associated with electricity generation and demand further aggravate the difficulties of the DSO

in real-time management. The situation becomes even worse in the case of islanded operation when the value of lost load (LL) is high, mostly, due to lacking uncertainty consideration. If RESs integration is unaccomplished, the MG does not retribute. Therefore, to have a reliable MG, a flexible demand side is necessary, which can be activated by demand response (DR) options [4]. DR has the tendency to complement the volatility of RESs. It is seen as a versatile tool that, depending on the system profile, acts as a power source or power sink to mitigate the demand supply gap [5].

A variety of DR approaches has been proposed in the literature to tackle RES intermittency, uncertainty and hedge high real-time electricity prices with a minimal comfort loss. DR loads mainly include electric water heater (EWH), heating, ventilation and air-conditioning (HVAC), dryers, electric vehicles, and electric and thermal storage devices. Among all the DR options, thermostatically controlled loads [6–14] such as HVAC and EWH, have received substantial attention in recent years. However, the majority of the proposed DR models were either too complex or had limited applications. For example, the EWH models proposed in [6,7] require too many measurements for scheduling. The flexibility offered by building thermal capacity using ground source heat pumps was analyzed in [11], where the application was limited due to its geographically independent nature. Authors in [13] devised a look-up table to evaluate the DR potential of HVAC loads which essentially demands a zig-bee sensor network, which is uneconomical from the MG aggregator's perspective.

In this paper, we study the flexibility offered by HVAC and EWH loads while exploiting building thermal masses, to match the load with intermittent RESs profile and address the uncertainties in a MG setting. The fundamental reason for selecting these loads is their highest contribution in the annual energy consumption profile of countries in the Nordic region, e.g., in Finland, due to long winters; the share of space heating load totals approximately 70% in the annual residential demand [15]. The idea underlying the HVAC response is that users usually tolerate a small deviation from the desired indoor temperature. Due to high thermal time constant of well insulated buildings in the Nordic region, HVAC loads can be scheduled to pre-heat or pre-cool buildings in order to cope with the intermittent nature of RESs or hedge against price spikes while respecting the end user comfort band. In this way, buildings act as a small storage buffer, thanks to building thermal inertia. Similarly, EWH is another potential candidate for DR and renders as a pre-requisite element for domestic hot water (DHW) usage. It accounts for the second largest energy consumption next to HVAC. The DHW reflects a higher flexibility, e.g., according to the Finnish building code, the maximum and minimum temperature limits are 65°C and 55°C, respectively.

Moreover, simultaneous generation and demand scheduling in an MG has recently attracted vast research attention, as it would provide an additional degree of freedom to the network operator. Several models have been developed to minimize the operating cost or maximize the revenue of MG while considering DR and participation in electricity markets as a prosumer. For instance, [16]

proposed an optimal framework to match the system's actual and desired load profiles by employing the distributed control of HVAC and EWH loads. The optimal energy trading in a community of interconnected MGs was reported in [17], where the proposed DR model did not account for user comfort, which is a crucial issue. The economic operation and reliability evaluation of a real MG was investigated in [18]. A shortcoming is that the component outages were scheduled in a deterministic manner that resulted in a major error. More recently, the work [19] focused on an energy scheduling mechanism in an existing non-isolated MG taking a fuzzy programming approach while analyzing non-responsive loads only. A dynamic optimal power flow of an industrial MG with a high population of electric vehicles was explored in [20]. An agent-based DR model was presented in [21] that aimed to reduce the system peak load and cost savings by trading between two grid-connected MGs.

Furthermore, several efforts have been dedicated to address the forecast errors and uncertainties in the real time energy management of a MG, since the economics and reliability are dependent on these factors. In this field, the work [22] considered a scenario-based optimization model (a pro-active approach) to address the uncertain parameters in a grid-connected MG operation. A stochastic frame-work was put forth in [23] to devise an optimal bidding strategy of a MG participating in a two-settlement market, while probing the flexible residential loads. Researchers in [24] presented a stochastic programming based Pareto objective function, to simultaneously minimize the MG operating cost and the carbon emissions.

However, the effectiveness of rolling horizon (RH) based energy management of an MG considering time shiftable loads in a 24-hour scheduling period, was analyzed in [25,26]. The study [25] also investigated the effect of RH length on the optimal solution. RH feedback, a reactive approach to uncertainty modelling, is an iterative method that assumes the information within a certain time frame is accurate. The input parameters are periodically updated through a feedback for the optimization. The decision variables are only implemented for the control horizon that is shorter than the prediction horizon. A similar approach called model predictive control was also employed to model uncertainty in islanded MG [27]. The contribution [28] utilized the DR capability of shiftable loads and compared the performance of discrete and hybrid time representations of the energy management model of MG. Similarly, dynamic programming (DP) or approximate DP is another newly accepted approach used to study the economic operation of an MG [29,30]. DP is a multi-time period optimization algorithm, which is solved recursively and it often suffers from high dimensionality problem. Although the solution can be approximated to near-optimal, it is computationally not efficient as it requires training through a large number of test scenarios, and comprehensive DR models further complicates the problem.

Our current research also belongs to coordinated generation and demand scheduling of MG with several distinct modelling features. To the best of the authors' knowledge, the following drawbacks still exist in this area of research: First, the previous studies on MG scheduling analyzed

the uncertainty based on either the pro-active approach (stochastic programming) or the reactive approach (RH) in a short term scheduling period. There is a great need to account for all the uncertainty aspects simultaneously in one model. Second, the majority of the proposed energy management models did not consider comprehensive DR that would include both the user comfort level and the penalty. Third, the effectiveness of the models was merely demonstrated for average conditions and, consequently, are incapable of taking into account the extreme or worst input conditions. Finally, the volatility in the uncertain parameters cannot be properly analyzed by merely examining a 24-hour period; instead, it requires longer study periods that would involve the random failure of MG components. Our work fills these critical gaps while the main contributions are highlighted as follows:

- We propose a comprehensive energy scheduling framework for islanded and interconnected operation of a renewable generation-based MG that incorporates bi-directional power exchanges with the grid subject to day ahead market prices, which is a common practice in Nordic countries [31–33]. The proposed method is novel in that the uncertainties are addressed within simultaneous pro-active and reactive approaches, while jointly probing the flexibility of HVAC units, EWH units, building thermal masses and BESS through central EMS.
- The proposed model is formulated as stochastic mixed integer linear program (MILP) aimed to minimize the MG operating cost while preserving households comfort levels. The model is simulated iteratively for each 24-hour RH over a one-year period. Hence, our model considers all simulation conditions including the most extreme ones. We compute risk indices to compare the simulation results of different cases as well as quantify the benefit of grid interconnection. Extensive sensitivity analysis is also conducted to determine the firm effect of various design parameters on the decision variables.
- Reliability aspects are considered in the RH in such a way that the availability status associated with only the first hour unfolds to the aggregator at the beginning of each RH. The status of different components for the remaining horizon (hour 2 to 24) remains the same as in the first hour. The statuses are then updated periodically according to Monte Carlo (MC) simulation in each horizon, thus speculating a practical case.

The rest of the paper is organized as follows. Section 2 discusses various models of MG components and reliability evaluation mechanisms. The problem formulation is described in Section 3. Case studies and simulation results are demonstrated in Section 4. Section 5 draws the conclusions.

2. SYSTEM MODEL

A. Microgrid

This work realizes a MG consisting of photo-voltaic (PV) system, a wind turbine (WT), a back-up diesel generator (DG), a battery energy storage system (BESS), and various households

equipped with individual HVAC and EWH systems. All other loads except HVAC and EWH are considered as critical. The operating cycle of the households' flexible loads are controlled by an aggregator via a centralized energy management system (EMS) which is connected to individual households through home EMS. Hence the aggregator knows the comfort preferences of individual households. Aggregator owns and schedules the storage and all supply sources in the MG that is also connected to the distribution grid and capable of exchanging power. In islanded mode, MG aggregator manages the system operation by optimizing the DG and BESS operations whereas in grid-connected mode, MG operates as a prosumer.

B. Distribution Grid

In the Helsinki metropolitan area, there are electricity retailers offering bilateral contracts for two-way electricity exchanges. Further, there are various options for electricity tariffs/contracts and the customer is free to choose among them [31–33]. In this work, we consider a bilateral spot price contract, [31], based on the electricity spot price of the Nord-Pool market (Elspot) [34]. In Nord-Pool, major transactions take place in Elspot market. The Nord-Pool publicly declares the hourly spot prices every day at noon, and these prices are applicable for the trade in the following day. According to this contract [31], a prosumer will pay for its energy usage according to the spot price, while it is subject to 24% value-added-tax (VAT). Moreover, there is a fixed premium for importing electricity [32,33]. Similarly, the retailers provide a compensation for the surplus electricity produced by the prosumer. The retailer buys the excess energy at the spot price but deducts a small commission [31].

C. Uncertainty Modelling

The main source of uncertainties in an MG are the input parameters, namely wind speed, solar irradiance and external temperature. These parameters directly affect the output of RESs and the operation of HVAC that is primarily driven by the external temperature. In practice, the aggregators obtain weather forecasts from a forecasting center, while, in this study, traditional time series method, i.e., ARIMA, is employed for an hourly-based forecast. Please note that there is no uncertainty in the Elspot prices and so as in spot price contracts offered by electricity retailers.

To model the uncertainty, both discrete scenarios (pro-active approach) and RH feedback (reactive approach) are considered in the optimization problem. Three equi-probable scenarios of each input parameter are generated to encompass the uncertainty in the pro-active approach. The scenarios are constructed so that the deviation among individual scenarios increases linearly through the prediction window of 24 hours, and is set to 10% at the end, as shown in Figure 1 [14]. Further, the RH method is employed that accounts for the error accumulation in the prediction horizon. Generally, the forecast error increases exponentially throughout the prediction horizon. Therefore, the forecast corresponding to later hours inside horizon are based on inaccurate information. The effectiveness of the RH forecast in decreasing the error is shown in Figure 2. For the sake of illustration, only 48 hours are considered. In the Figure, the continuous line indicates the actual

temperature values, while the dashed lines represent the forecasts obtained in each hour for the following 24 hours. In the case of the conventional forecast, when the forecast for the next 24 hours is done at hour 1, the error may drastically increase when the time passes. In this case, the maximum error occurs at hour 14 with a 59.5% deviation. On the other hand, the largest forecast error using the rolling window is 5%, occurring in hour 19, which is negligible compared to the conventional approach. It is also visible that the forecast corresponding to the first hours in each rolling window is the most accurate and, in some cases, it almost matches the actual value, which verifies the effectiveness of this methodology.

Figure 1. An example of scenarios of hourly temperature in the optimization horizon

Figure 2. Rolling horizon temperature forecast for a day of Spring

D. Reliability Evaluation

A two-state discrete time Markov chain process is applied to represent the available and unavailable states of the MG components for each time slot in a one year period. Random outages of each component are simulated by the MC method. The failure and repair times of power equipment follow the exponential distributions with parameters $1/\lambda$ and $1/\mu$ respectively which are adopted from [35,36]. All the components are assumed independent and initially available. It is assumed that the components' state remains unchanged throughout the optimization horizon of 24 hours, i.e., in any horizon, if a component is available in the beginning of that horizon then it would be available for the entire horizon lasting 24 hours. The availability status of each component is updated in the next horizon according to MC simulation. With such modelling, the aggregator is unaware of the contingency events beforehand.

3. PROBLEM FORMULATION

The proposed formulation leans on simultaneous scheduling of MG production and consumption while considering RH feedback, stochasticity and random outages. The approach also contemplates DR for continuously operated flexible loads and electric storage, with the facility of power exchanges with the distribution grid. The inputs include weather forecasts, thermal preferences of end-users, day ahead prices, BESS initial state of charge (SOC), and initial commitment status of DG unit along with components' availability status. The optimal decision variables include the expected power levels of the HVAC units, EWH units, indoor ambient temperature, building mass temperature, DHW temperature, BESS charging/discharging power, curtailed energy, DG output, and the power exchanges with the distribution grid in each hour and for each scenario. Needless to mention that the proposed problem is not a bidding problem and the considered MG is a price taker.

A. Objective Function

The objective of the MG aggregator is to minimize the total operating cost in each 24-hour horizon over all scenarios while satisfying the demand and supply constraints. It is given as follows:

$$\min \sum_{s \in S} \rho_s \left[\sum_{h \in H} \left\{ \begin{aligned} & \left(SU_{s,h} + SD_{s,h} + C(P_{s,h}^g) \right) + D^{bess} \cdot \left(\eta_c P_{s,h}^{b,ch} + \frac{P_{s,h}^{b,dch}}{\eta_d} \right) + V^{LG} \cdot LG_{s,h} \\ & + V^{LL} \cdot LL_{s,h} + \sum_n \theta_h^n \left(|T_{s,h}^{a,n} - T_{set}^{hvac}| \right) + \sum_n \phi_h^n \left(|T_{s,h}^{dhw,n} - T_{set}^{dhw}| \right) \\ & + \left((1 + \delta) \lambda_h^{DA} + \psi \right) \cdot P_{s,h}^{import} - \left(\lambda_h^{DA} - \omega \right) \cdot P_{s,h}^{export} \end{aligned} \right\} \right] \quad (1)$$

where ρ_s denotes the probability of a scenario s . The operating cost (1) includes eight terms. The first term, $(SU_{s,h} + SD_{s,h} + C(P_{s,h}^g))$, corresponds to the DG cost. DG cost further comprises fixed start-up, shut-down and variable cost of production in time slot h and scenario s . The term

$D^{bess} \left(\eta_c P_{s,h}^{b,ch} + \frac{P_{s,h}^{b,dch}}{\eta_d} \right)$ captures the BESS degradation cost due to charging and discharging cycles.

The third term, $V^{LG} LG_{s,h}$, considers the penalty due to generation curtailment while the fourth term, $V^{LL} LL_{s,h}$, accounts for the penalty due to total load curtailments in an MG. The term

$\sum_n \theta_h^n \left(|T_{s,h}^{a,n} - T_{set}^{hvac}| \right)$ represents the total thermal discomfort cost imposed by households due to deviation from HVAC set point temperature within the specified individual comfort band in time step h and scenario s . The MG aggregator will pay each household proportional to the deviation of indoor ambient temperature from its respective set point. The parameter θ_h^n expresses the willingness of the household n to trade its thermal comfort for cost savings in time step h . The narrow temperature comfort band and high value of penalty factor θ_h^n represent the households with a strict comfort

requirement, thus offering less flexibility to the aggregator. Similarly, the next term, $\sum_n \phi_h^n \left(|T_{s,h}^{dhw,n} - T_{set}^{dhw}| \right)$, describes the total discomfort cost due to deviation from DHW priority in time step h and scenario s . Households have the freedom of tuning both the individual temperature dead band and penalty factors to participate in the DR program. The 7th term, $\left((1+\delta) \cdot \lambda_h^{DA} + \psi \right) P_{s,h}^{import}$, specifies the cost of energy purchased from the distribution grid. This cost has two components such as the hourly day-ahead price considering VAT, and the fixed distribution tariff. The last term, $\left(\lambda_h^{DA} - \omega \right) P_{s,h}^{export}$, represents the revenue of surplus power sold to the grid at a tariff equal to the spot price minus the commission ω . This last term is the only profit earned by the aggregator.

To recognize the associated benefits of the RESs, a zero operating cost is assumed for the RESs, however, a small cost is allocated to spillage of RESs, hence first, the aggregator tries to satisfy the demand with the RESs' while the excess demand can be balanced with other sources. For *LL*, the maximum limit is not set, however, a very high penalty (V^{LL}), in the objective is set. Moreover, a realistic V^{LL} is taken from [37], which is based on macro-economic concept. The proposed objective (1) is subject to the following constraints:

B. Photovoltaic Output

A model that involves the irradiance and temperature as input is used [38]. The essential parameters may be found from the manufacturer's datasheet. The model is presented in (2)-(3).

$$P_{s,h}^{PV} = \frac{PV_{\max} \cdot G_{s,h}}{G_{ref}} \cdot \frac{\ln(I_{sc})}{\ln\left(\frac{I_{sc}}{G_{s,h}} G_{ref}\right)} \cdot \frac{T_{jref}}{T_j} \quad (2)$$

$$T_j = T_{s,h}^{ext} + \frac{NOCT - 20}{80} \cdot S_i \quad (3)$$

C. Wind Turbine Output

A practical model which approximates the power production curve to two straight lines is used in this work as given in (4) [39].

$$P_{s,h}^{WT} = \begin{cases} \frac{P_r}{w_r - w_c} \cdot (w_{s,h}^w - w_c), & w_c < w_w \quad \& \quad w_r > w_w \\ P_r, & w_{s,h}^w \geq w_r \\ 0, & w_{s,h}^w \leq w_c \end{cases} \quad (4)$$

D. Electric Water Heater

The physical model proposed in [9] is followed in this work. The temperature of DHW at hour ' h ' inside a tank may be calculated as in (5). For the sake of simplicity, thermal losses are ignored. The DHW usage action triggers the operation of EWH to maintain the DHW temperature inside the tank. However, the users may allow a small deviation from the set point to participate in the DR program offered by the aggregator. In this regard, the EWH may be scheduled at any time slot regardless of the usage profile concerning the comfort levels of each user. The DHW temperature

must remain in specified comfort limits as in (6). For simplicity, it is assumed that EWH can operate at any continuous level bounded by the maximum rating in (7).

$$T_{s,h}^{dhw,n} = \frac{T_{s,h-1}^{dhw,n}(V_{\tan k}^n - V_{use,h}^n \Delta h)}{V_{\tan k}^n} + \frac{T_{in} V_{use,h}^n \Delta h}{V_{\tan k}^n} + \frac{P_{s,h}^{ewh,n}}{c_w V_{\tan k}^n} \cdot \frac{\Delta h}{60 \frac{\min}{h}}, \forall s \in S, \forall h \in H, \forall n \in N \quad (5)$$

$$T_{s,h}^{dhw \min,n} \leq T_{s,h}^{dhw,n} \leq T_{s,h}^{dhw \max,n}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (6)$$

$$0 \leq P_{s,h}^{ewh,n} \leq P_{s,h}^{ewh \max,n}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (7)$$

E. Two-Capacity Building Model

A wide variety of thermodynamic models have been proposed in the literature to estimate heating or cooling loads [40–42]. Complex models are burdensome for practical applications, while very simple models do not produce accurate results. Therefore, a trade-off between accuracy and simplicity is required. In this work, a very efficient two-capacity building model to estimate the heating or cooling requirement that analyzes the indoor temperature variation with respect to the external temperature is used [14,15,43]. As can be seen in Figure 3, it uses two heat capacitances. One capacitance is allocated to the building mass, C^m , whereas the other is distributed to the indoor air, C^a . This model has two unknown temperatures, T^a and T^m .

Figure 3. Two-capacity building model prototype.

It is assumed that the HVAC unit, responsible for the ventilation air flows, is set to operate at a constant temperature, T^x . The generated air is of the convective type and is allocated to the indoor air node. For heat flows, T^s needs to be considered. The windows installed in the building have a small thermal mass compared to the building structure. The node points, T^e , T^a , T^m , T^s and the HVAC unit are connected through heat conductance or, whenever there is heat flow, they are connected by heat capacity. The building mass node is located at an undefined depth inside the building and hence embodies the mean temperature of the building mass [14]. The energy balance of this model is represented by a simplified discrete form as follows.

$$T_{s,h}^{a,n} = \frac{T_{s,h-1}^{a,n} + \frac{\Delta h}{C^a} (H^m T_{s,h-1}^{m,n} + H^e T_{s,h}^e + H^g T^g + H^x T^x + Q_{s,h}^{hvac,n})}{1 + \frac{\Delta h}{C^a} (H^m + H^e + H^g + H^x)}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (8)$$

$$T_{s,h}^{m,n} = \frac{T_{s,h-1}^{m,n} + \frac{\Delta h}{C^m} (H^m T_{s,h-1}^{a,n} + H^y T_{s,h}^e)}{1 + \frac{\Delta h}{C^m} (H^m + H^y)}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (9)$$

The unknown building parameters in (8) and (9) were identified by comparing the step response of IDA¹ model and the two-capacity model. The HVAC power was followed by a six-hour interruption resulting in exponential decay of T^u . The parameters were determined by minimizing the difference between the response from IDA and two-capacity model. Table 1 lists the unknown building parameters derived from [44]. Note that these parameters are applicable to Finnish detached houses with medium weight structures and insulated according to Finnish building code C3. Constraint (10) bounds the indoor temperature in a predefined dead band tunable by the occupants. HVAC unit can consume any power level between 0 and maximum level as expressed in (11).

$$T_{s,h}^{set,n} - \frac{\sigma^n}{2} \leq T_{s,h}^{a,n} \leq T_{s,h}^{set,n} + \frac{\sigma^n}{2}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (10)$$

$$0 \leq |Q_{s,h}^{hvac,n}| \leq Q^{\max,n}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (11)$$

The absolute function in (11) appears due to the fact that $Q_{s,h}^{hvac,n}$ in (8) takes on positive values in heating mode, i.e., when the external temperature is lower than the HVAC set point temperature, and takes negative values in cooling mode. The absolute function renders it a non-linear model and the existing approaches or commercial solvers cannot guarantee a global optimal solution. Hence, this non-linear term is linearized using two positive auxiliary variables. Since the absolute value function does not appear in the objective (1), binary variables are employed to ensure the accuracy of the solution. Equations (12) – (16) take care of the absolute function appearing in constraint (11) as follows:

$$Q_{s,h}^{hvac,n} = Q_{s,h}^{a,n} - Q_{s,h}^{b,n}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (12)$$

$$|Q_{s,h}^{hvac,n}| = Q_{s,h}^{a,n} + Q_{s,h}^{b,n}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (13)$$

$$Q_{s,h}^{a,n} \leq b_{s,h}^{a,n} Q^{\max,n}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (14)$$

$$Q_{s,h}^{b,n} \leq b_{s,h}^{b,n} Q^{\max,n}, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (15)$$

$$b_{s,h}^{a,n} + b_{s,h}^{b,n} \leq 1, \quad \forall s \in S, \forall h \in H, \forall n \in N \quad (16)$$

Table 1. Two-capacity model parameters.

Parameter	Unit	Value
H^e, H^f, H^m, H^g, H^x	W/°C/m ²	0.29, 0.33, 5.16, 0.48, 0.05
C^a, C^m	W.h/°C/ m ²	3.616, 31.14
T^g, T^x	°C	10, 18

¹ IDA is a simulation tool to study the indoor environment and energy consumption of a building

F. Diesel Generator

The quadratic cost function of a conventional DG is usually approximated by a piece-wise linear function [45]. The operating cost of DG is modeled as follows.

$$C(P_{s,h}^g) = a_{s,h} + \sum_m \alpha^m P_{s,h}^m, \forall s \in S, \forall h \in H \quad (17)$$

$$0 \leq P_{s,h}^m \leq P_{s,h}^{m,\max}, \forall s \in S, \forall h \in H \quad (18)$$

$$P_{s,h}^g = P_{s,h}^{g,\min} I_{s,h} + \sum_m P_{s,h}^m, \forall s \in S, \forall h \in H \quad (19)$$

$$P_{s,h}^{g,\min} I_{s,h} \leq P_{s,h}^g \leq P_{s,h}^{g,\max} I_{s,h}, \forall s \in S, \forall h \in H \quad (20)$$

Moreover, the constraints (21), (22) ascertain the relationship between production level and ramp limits during different transitions. Equations (23) - (24) state that DG should consider a start-up and shut-down cost apart from the operating cost.

$$P_{s,h}^g - P_{s,h-1}^g \leq P_{s,h}^{g,\min} (2 - I_{s,h} - I_{s,h-1}) + RU(1 + I_{s,h-1} - I_{s,h}), \forall s \in S, \forall h \in H \quad (21)$$

$$P_{s,h-1}^g - P_{s,h}^g \leq P_{s,h}^{g,\min} (2 - I_{s,h} - I_{s,h-1}) + RD(1 - I_{s,h-1} + I_{s,h}), \forall s \in S, \forall h \in H \quad (22)$$

$$SU_{s,h} \geq CU_{s,h} (I_{s,h} - I_{s,h-1}), \forall s \in S, \forall h \in H \quad (23)$$

$$SD_{s,h} \geq CD_{s,h} (I_{s,h-1} - I_{s,h}), \forall s \in S, \forall h \in H \quad (24)$$

G. Battery Energy Storage System

The charging and discharging power of the BESS is bounded in (25)-(26), and to prevent simultaneous charging and discharging, binary decision variables are constrained as in (27).

$$0 \leq P_{s,h}^{b,ch} \leq b_{s,h}^{ch} \cdot P^{ch,\max}, \forall s \in S, \forall h \in H \quad (25)$$

$$0 \leq P_{s,h}^{b,dch} \leq b_{s,h}^{dch} \cdot P^{dch,\max}, \forall s \in S, \forall h \in H \quad (26)$$

$$b_{s,h}^{ch} + b_{s,h}^{dch} \leq 1, \forall s \in S, \forall h \in H \quad (27)$$

The SOC of the BESS in any time slot 'h' may be determined by the constraint (28) while (29) bounds the state of charge for the purpose of increasing the life cycle.

$$SOC_{s,h} = SOC_{s,h-1} + \eta_c P_{s,h}^{b,ch} - \frac{P_{s,h}^{b,dch}}{\eta_d}, \forall s \in S, \forall h \in H \quad (28)$$

$$SOC^{\min} \leq SOC_{s,h} \leq SOC^{\max}, \forall s \in S, \forall h \in H \quad (29)$$

H. Power Exchange with the Distribution Grid

The power exchange is capped either by a contracted amount in the spot price contract or by thermal rating of the conductor. The limits of imported and exported power may be different, however, in this work, the same limits are assumed.

$$P_{s,h}^{export} \leq P^{grid,\max}, \quad P_{s,h}^{import} \leq P^{grid,\max}, \quad \forall s \in S, \forall h \in H \quad (30)$$

I. Power Balance

$$P_{s,h}^g + P_{s,h}^{PV} + P_{s,h}^{WT} + P_{s,h}^{b,dch} + P_{s,h}^{import} + \sum_n (LL_{s,h}^n) = \sum_n (|Q_{s,h}^{hvach,n}| + P_{s,h}^{ewh,n} + F_h^n) + P_{s,h}^{b,ch} + P_{s,h}^{export} + LG_{s,h}, \quad \forall s \in S, \forall h \in H \quad (31)$$

The LG is always smaller than the sum of the available output power from RESs and DG.

$$LG_{s,h} \leq P_{s,h}^{PV} + P_{s,h}^{WT} + I_{s,h} P^{g,\min}, \quad \forall s \in S, \forall h \in H \quad (32)$$

J. Loss of Load Probability

This grid index determines the probability the demand will exceed the supply in a given time period. It is calculated over all 27 scenarios as in (33).

$$LOLP = \sum_s \rho_s T_s^{LL}, \quad \forall s \in S \quad (33)$$

Figure 4. Block diagram for the proposed framework

The proposed methodology is sketched in Figure 4 using a flow diagram. The simulation period contains 8760 hours. The proposed model starts at hour $h=0$. The input parameters for next 24 hours are forecasted and three probable scenarios for each parameter (as shown in Figure 1) are generated which are fed to the models discussed earlier in the preceding sub-sections. The input scenarios, critical loads, initial parameters, availability statuses and the households' preferences are loaded in GAMS for stochastic optimization. The decision trajectories for 24 hours are obtained but only the first hour decisions are retained. The forecasted parameters, for the next 24 hours are updated based on the most recent information available (as shown in Figure 2) and the whole process is repeated again till the end of the year.

4. CASE STUDIES

A. Simulation Parameters

This work considers an MG consisting of 50 heterogeneous households served by an aggregator. Each household consists of a single family, residing in a 2-floor detached house and equipped with a HVAC unit, EWH unit, and critical load. The aggregator is aware of individual load

parameters and comfort priorities via the EMS. The variance among households is captured by uniformly distributing the load parameters and comfort limits as detailed in Table 2. The fixed load is forecasted based on the AMR data of residential households in Helsinki.

It is assumed that a household's daily DHW profile remains unchanged throughout the year. It is a good assumption since the monthly variation factor for DHW usage in Finland is between 0.9 and 1.1 [46]. The DHW profile is depicted in Figure 5 [15]. The HVAC set point temperature for all households is 21°C, and the DHW preference is set to 60°C. To analyze the worst case, building occupancy is taken as continuous over the study period. The discomfort penalty within the comfort band is set to $\theta_h^n = \phi_h^n = \epsilon 0.02/^\circ\text{C}/\text{hour } \forall n \ \& \ \forall h$. The initial indoor and thermal mass temperature are assumed equal to the set point temperature $\forall n$. Similarly, the initial temperature of DHW is set to 60°C $\forall n$. The DHW consumption in Figure 5 is uniformly distributed around its mean to create diversity among households. A high $V^{LL} = \epsilon 4.11/\text{kWh}$ [37], is set, while $V^{LG} = \epsilon 0.01/\text{kWh}$.

Table 2. Input parameters of the MG

Parameter	Symbol	Unit	Households (n)	Numerical Distribution
Total area of house	A^n	m ²	1:50	[175, 225]
Power rating of HVAC	$Q^{\max,n}$	kW	1:50	[6, 7]
Indoor temperature limits	$T_{set}^{hvac} - \frac{\sigma^n}{2}, T_{set}^{hvac} + \frac{\sigma^n}{2}$	°C	1:15	[20.5, 21.5]
			16:35	[20, 22]
			36:50	[19.5, 22.5]
Power rating of EWH	$P^{ewh\max,n}$	kW	1:50	[1.5, 2]
Volume of hot water tank	$V_{\tan k}^n$	dm ³	1:50	[175, 225]
DHW temperature limits	$T_{s,h}^{dhw\min,n}, T_{s,h}^{dhw\max,n}$	°C	1:15	[58.5, 61.5]
			16:35	[57, 63]
			36:50	[55.5, 64.5]

Figure 5. Daily domestic hot water consumption profile in Finland.

The generation portfolio of the MG consists of the following technologies:

- PV system: $PV_{\max}$ of complete PV string is 400 kW, where $NOCT = 45^\circ\text{C}$, efficiency = 21%.
- WT unit: $P_r = 400$ kW, $w_c = 3\text{m/s}$ and $w_r = 14$ m/s.
- DG set: One backup DG with $Pg_{\max}$ of 150 kW and $Pg_{\min} = 15$ kW, $a = \epsilon 6/\text{h}$. A quadratic cost function is considered with 9 segments of 15 kW each.
- BESS: Capacity is 200 kWh with $P^{ch,\max} / P^{dch,\max}$ of 60 kW. The initial SOC is set to 50%, while it can hover in the range [10, 90]% of capacity, $D^{bess} = \epsilon 0.002/\text{kWh}$, and $\eta_c = \eta_d = 0.9$
- Distribution Grid: The limit for import and export is 100 kW. The fixed distribution fee is ϵ

0.0361/kWh with 24% VAT, the retailer commission is € 0.0024/kWh.

The external temperature and solar irradiance are forecasted using historical weather data of Helsinki [47]. The wind speed is predicted at 40 meters of height [48]. The inputs corresponding to the first hour of each RH are illustrated in Figure 6. We use the historical day-ahead prices for the year 2017 [34] depicted in Figure 7. Table 3 lists the outage events of the MG components simulated via MC method, where the second row details the starting and ending hours of the random outage. For a fair comparison, the same events are considered for all case studies.

Figure 6. (a). Hourly temperature forecast. (b) Hourly PV output. (c) Hourly wind turbine output.

The simulation period starts from Jan-01 and ends on Dec-31. The optimization is performed for 24 hours ahead over all 27 equi-probable scenarios (the probability of each scenario is $1/27$) while considering 50 households with time resolution of one hour. Therefore, the MILP problem consists of 234,576 continuous variables and 66,744 binary variables per each 24-hour horizon. The model is solved in a desktop computer with 3.4GHz Intel Xeon processor and 16 GB RAM, while is simulated on GAMS-MATLAB environment and solved using the CPLEX. The average CPLEX time per iteration is about 2.5s.

Figure 7. Hourly spot price for year 2017(Includes fixed distribution fee and VAT).

Table 3. Outage statistics of the MG components by MC simulation

Component	PV	WT	DG	BESS	Transmission Line
Outage Event (Start and end hour)	980-1017, 6156-6191	3409-3437, 7306-7331	1213-1244, 4413-4448, 7958-7980	4013-4021	8277-8282

B. Simulation Results

In order to show the effectiveness of the proposed model, we simulate both the islanded and grid connected operations with and without DR coordination as detailed below:

- *Case I:* The operation of an islanded MG is optimized under no DR control, i.e., constraints (6), (10) and (30) are disregarded implying that neither deviation from set point temperatures is allowed nor power exchanges with the grid take place. The objective function in (1) does not include the last four terms.
- *Case II:* The proposed DR scheme is applied to an islanded MG. Here, the thermal comfort bounds (6) and (10) for DR loads, i.e., HVAC and EWH are considered, while disregarding the last two terms in (1) and constraint (30).
- *Case III:* This case is similar to Case I except that the last two terms in (1) and constraint (30) are included for grid-connected operation without DR.
- *Case IV:* This case takes into account the complete model, (1)–(33), for a grid-connected MG.

The above mentioned case studies are simulated and the results are discussed hereinafter. Figure 8 depicts the simulated load profile for Case I. The maximum and average hourly load of the MG are 328.5 kW and 124.2kW, respectively. Aggregator minimizes the cost by coordinating the operation of BESS and DG only. The total *LL* stands for about 4.02% of the total demand and the operating cost is € 300,360. Figure 8 corroborates that the HVAC load directly follows the variation in external temperature illustrated in Figure 6(a), and it is also obvious from the fact that the highest load occurs when the lowest temperature is experienced. Contrarily, the EWH loads follow the same pattern over the year since the daily DHW profile for each household is assumed constant. The fixed load, mainly the illumination and appliances, shows some seasonal behavior.

Figure 8. Hourly load of all households (Case I).

Figure 9. Hourly optimal expected loads for islanded MG under DR (Case II).

Figure 9 presents the load profile for Case II when the proposed MG is simulated with DR control in islanded mode. Please note that the proposed methodology may slightly alter the annual demand since demand conservation is not our objective, nevertheless, the comfort preferences must remain unscathed. Simulation results for Case II prove that the HVAC loads are more flexible compared to the EWH loads. The main reason of this phenomenon is the limited usage of DHW (see Figure 5), which is in contrary to the HVAC load due to maintaining the ambient temperature all the time. The high ramp-rate of the HVAC load in conjunction with building thermal inertia enables to cope effectively with the RESs intermittency. This ramp rate is proportional to the thermal comfort band of the individual household. The wider the band, the higher is the energy transitions in HVAC profile. In order to maintain thermal comfort, building thermal masses release energy when HVAC loads reduces consumption due to low output of RESs. Unsurprisingly, in Figure 9, the maximum demand has increased from 328.45kW to 374.18 kW, which is justified as follows. The WT production is at the rated level and the PV output is also ample in that hour whereas the RESs output significantly drops in the subsequent hours. In order to respect the thermal priorities while optimizing the cost, the HVAC units are operated close to the upper comfort limits during the periods in which the RESs output is high and recoups for energy consumption at later hours, i.e., building thermal masses store energy. Figure 10 animates the optimal energy curtailments for this scheme. The total *LL* reduced to 2.89% of the annual demand and annual cost is reduced to € 229,160.

Figure 10. Optimal expected lost load and lost generation for islanded MG under DR (Case II).

Next, we simulate the MG with the capability of exchanging power via a bilateral spot price contract but without considering DR i.e. Case III. To streamline our study, it is assumed that at every time step, the MG aggregator is always aware of the next 24-hour prices. Note that under no DR management, the load profile remains the same as in Case I but the cost is reduced extremely due to the benefit of the spot price contract which is two-fold: 1) it brings more flexibility to the aggregator as there are no operational constraints associated with the exchanges except $P_{grid,max}$, and 2) the excess production from the RESs may be exported at a favorable price. Due to power exchanges in Case III, the cost is reduced to € 73,728. The coordination of DR with spot price contract, i.e., Case IV yielded even better outcomes. It resulted in increased utilization of building thermal masses, which is confirmed by comparing HVAC consumption in Figures 9 and 11. The power exchanges subsided by DR leads to significant cost savings in the form of reduction in curtailments that are demonstrated in Figure 12. Note that LL and LG still prevails in winter and summer seasons, respectively after utilizing the full exchange capability. The annual cost savings are 24.12% compared to Case III.

Figure11. Hourly optimal expected loads for grid connected MG under DR (Case IV).

The numerical results obtained for different case studies are summarized in Table 4. Note that RESs profile is the same for all cases. The values or economical advantages of the grid interconnection can be seen in this table. For the aggregator, Case III yields 75.45% cost savings compared to Case I and 68.72% savings with respect to Case II wherein DR is unleashed. Similarly, Case IV awards 81.4%, 75.6% and 24.12% cost savings compared to Cases I, II and III respectively. In addition, the progress in LOLP is 89.7%, 83% and 42% relative to Cases I, II and III respectively. This advancement in LOLP positively affects the quality of electricity supply and comfort for the

households. It is also observable that DR slightly reduces the consumption in Cases II and IV at some cost borne by the aggregator.

Figure 12. Benefits of the DR and EMS for Case IV (a)Energy curtailments (b)Power exchanges.

Table 4. Comparison of results for different case studies

Expected Decision Variable	Case I Islanded MG without DR	Case II Islanded MG with DR	Case III Grid-connected MG without DR	Case IV Grid-connected MG with DR
MG cost (€)	300,360	229,160	73,728	55,877
LOLP (%)	9.84	5.97	1.74	1.01
Consumption (MWh)	1087.9	1032.2	1087.9	1045.7
Lost Load (MWh)	43.06	29.92	6.02	3.984
Lost Generation (MWh)	387.42	354.9	124.86	100.61
DG production (MWh)	388.25	313.49	93.68	61.73
BESS charging (MWh)	34.79	36.84	50.58	43.26
BESS discharging (MWh)	28.1	29.69	40.89	35.02
Exports (MWh)	-	-	261.2	260.25
Imports (MWh)	-	-	332.95	298.01

It is worth mentioning that the higher ratings of DR loads are more economical from aggregator's perspective as they accommodate higher intermittency of RESs by consuming more power when the RESs output is high, however, for the households, the investment in flexible loads primarily depends on the monetary benefits offered by aggregator to participate in DR program. Further, a part of the benefit is also restricted by the households comfort priorities. A wider thermal comfort band and lower penalty would bring more savings to the aggregator. When selling power to the grid, the aggregator has to accomplish rational trade-offs between increasing the exported power and bearing the discomfort cost due to households' comfort priorities. It certainly depends on the amount of available RESs and the electricity spot prices.

To demonstrate the effectiveness of the proposed framework, one probable scenario of the

grid-connected operation (Case III and Case IV) for two consecutive days of winter is depicted in Figure 13. Note that the presented decisions correspond to the first hour in each RH. It is evident from Figure 13 (b) that the DR aims to match the RESs profile closely where the gap between the optimized demand and RESs, is much smaller than the case without DR, in Figure 13 a, and sometimes they overlap. BESS operation is limited due to the high ramping capability of building thermal masses. Contrarily, BESS operation is more demanding under no DR control in Case III. Moreover, DR not only prevents the DG commitments in Figure 13(b) but also aims to reduce the imported power when the price is relatively higher, in hours 3-6. The excess RESs are either exported or used to charge the BESS, but in Fig 13 (a) at hour 12, the BESS is charging from excessive DG production. It is due to the imperfect information at this hour which is updated later in RH feedback, and the 24-hour forecast could not assess the availability of excess RESs output. This is an example of how the aggregator bears cost due to the imperfect information in MG operation and how the RH feedback tries to minimize this cost.

Figure 13. One scenario of grid-connected MG operation (a) Case III (b) Case IV.

a. Sensitivity Analysis

Finally, we analyze the impact of various MG parameters such as $P_{grid,max}$, θ_h^n , ϕ_h^n , and BESS capacity, on Case IV. Figure 14 illustrates the effects of varying $P_{grid,max}$ where the expected cost of MG and the curtailments decrease as the exchange capacity increases. By increasing $P_{grid,max}$, the aggregator earns more revenues by exporting the surplus energy from the RESs and mitigating the

LL by importing more power. Higher $P_{grid,max}$ also eliminates the requirement of DG operation during critical hours. In Figure 14(a), the maximum improvement results when $P_{grid,max}$ changes from 0 to 50kW thereby reducing the cost by 49.78%, from €229k to €115k. This transition of cost clearly implies the benefit of the spot price contract supported by the grid-interconnection facility. The cost is saturated when $P_{grid,max}$ exceeds 200 kW and the main reason is that the majority of the curtailments range between 0 and 200 kW without the interconnection facility, as can be seen in Figure 10 that shows the curtailments of islanded MG under DR control. It was discussed earlier that the DR benefit is constrained by limited load ratings and comfort constraints, hence higher $P_{grid,max}$ is the key factor in reducing the operating cost. Based on $P_{grid,max}$, the aggregator can invest in RESs to sell more energy and thus transform the annual cost into net profit, i.e., negative cost in our model.

Figure 14. Effect of varying $P_{grid,max}$ (a) MG cost, LOLP (b) Energy curtailments

Figure 15 demonstrates the evolution of MG cost and curtailments versus thermal discomfort penalty factors. The higher θ_h^n, ϕ_h^n increase the MG cost since by increasing these factors, the DR loads tend to operate closer to their temperature set points, thus bring down the discomfort cost and providing less flexibility to the aggregator. It results in more imports, and hence less exports to the grid. Besides, LL decreases marginally while LG increases drastically as DR loads are restrained to consume excess RESs. The MG cost mainly increases due to the higher LG which is much prevalent in summer season. Also, the HVAC load is negligible and less flexible in summer as the external temperature is oscillating around the set point temperature. An interesting observation is that the MG cost remains unchanged when discomfort penalty increases from 0.01 to 0.02€/°C/h. This implies that the cost due to V^{LG} is still dominating during this transition. Afterwards, the cost increases almost

linearly. When penalty is sufficiently large, the change in MG variables becomes insignificant, implying that the DR loads are operating at their desired set points most of the time and MG is utilizing the maximum potential of $P_{grid,max}$. At this stage, the cost is still lower compared to that in Case III.

Figure 15. Effect of varying thermal discomfort penalty (a) MG cost, LOLP (b) Energy curtailments.

Lastly, the impacts of varying BESS capacity on the proposed MG is illustrated in Figure 16. Results demonstrate that BESS brings significant cost savings only when the storage capacity is up to 300kWh after which the benefits start to saturate. It is also evident that the storage buffer offered by building thermal masses is more effective than the BESS. The increase in cost is just 6.2% when the BESS is not considered in Case IV.

Figure 16. Effect of varying BESS capacity.

5. CONCLUSIONS

In this paper, an energy management framework of MG based on simultaneous RH and

stochastic programming has been proposed that aims to minimize the operating cost while preserving the comfort preferences of heterogeneous households. The HVAC loads in coordination with building thermal inertia, and the DHW consumption altogether aids to achieve a rational trade-off between the energy curtailments and comfort priorities. Extensive simulation results for both islanded and grid-connected operation of an MG demonstrated the effectiveness of the topology. Results prove that the coordinated operation of thermal masses and DR loads bring significant cost savings over a one year period, by mitigating expensive DG commitments and closely matching the demand with intermittent RESs in both islanded and grid-connected modes. With the given MG parameters and the uncertainty, the proposed framework ensures 24.12% savings compared to the grid-connected operation without DR for a one year period. Spot price contract could be used to convert the operating cost into annual profit. Consequently, it is beneficial for the aggregator to invest on the RESs to support the utility grid through a sustainable approach. Moreover, higher discomfort penalty affects the overall cost but the DR benefits are still significant at sufficiently high penalty. Thermal masses are proved to be more dynamic and effective storage facility than the BESS, and therefore, BESS can be omitted if the DR load ratings are high enough to supplement the benefit. This study certifies that a practical model of such MG is definitely worthwhile where the retailers are willing to purchase excess productions of the RESs owned by end-users and/or participate in the electricity market, just like in the Nordic countries. The negative spot price during high generation hours can bring more cost savings to the MG aggregators.

ACKNOWLEDGEMENT

This work was supported by Aalto University as part of the Finnish Solar Revolution (FSR) project organized by ‘Business Finland’.

REFERENCES

- [1] O.D. Melgar Dominguez, M. Pourakbari-Kasmaei, J.R.S. Mantovani, Adaptive Robust Short-Term Planning of Electrical Distribution Systems Considering Siting and Sizing of Renewable Energy-based DG Units, *IEEE Trans. Sustain. Energy*. (2018) 1–1. doi:10.1109/TSTE.2018.2828778.
- [2] J.M.H. Ortiz, M. Pourakbari-Kasmaei, J. López, J.R.S. Mantovani, A stochastic mixed-integer conic programming model for distribution system expansion planning considering wind generation, *Energy Syst.* (2018). doi:10.1007/s12667-018-0282-z.
- [3] M.F. Zia, E. Elbouchikhi, M. Benbouzid, Microgrids energy management systems: A critical review on methods, solutions, and prospects, *Appl. Energy*. (2018). doi:https://doi.org/10.1016/j.apenergy.2018.04.103.
- [4] M. Marzband, M.H. Fouladfar, M.F. Akorede, G. Lightbody, E. Pouresmaeil, Framework for smart transactive energy in home-microgrids considering coalition formation and demand side management, *Sustain. Cities Soc.* 40 (2018) 136–154. doi:10.1016/j.scs.2018.04.010.
- [5] T. Müller, D. Möst, Demand Response Potential: Available when Needed?, *Energy Policy*. 115 (2018) 181–198. doi:https://doi.org/10.1016/j.enpol.2017.12.025.
- [6] M.J. Booyesen, A.H. Cloete, Sustainability through Intelligent Scheduling of Electric Water Heaters in a Smart Grid, in: 2016 IEEE 14th Intl Conf Dependable, Auton. Secur. Comput. 14th Intl Conf Pervasive Intell. Comput. 2nd Intl Conf Big Data Intell. Comput. Cyber Sci. Technol. Congr., 2016: pp. 848–855. doi:10.1109/DASC-PICom-DataCom-CyberSciTec.2016.145.
- [7] P.J.C. Nel, M.J. Booyesen, B. van der Merwe, A Computationally Inexpensive Energy Model for Horizontal Electric Water Heaters With Scheduling, *IEEE Trans. Smart Grid*. 9 (2018) 48–56. doi:10.1109/TSG.2016.2544882.
- [8] P. Du, N. Lu, Appliance Commitment for Household Load Scheduling, *IEEE Trans. Smart Grid*. 2 (2011) 411–

419. doi:10.1109/TSG.2011.2140344.

- [9] S. Shao, M. Pipattanasomporn, S. Rahman, Development of physical-based demand response-enabled residential load models, *IEEE Trans. Power Syst.* 28 (2013) 607–614. doi:10.1109/TPWRS.2012.2208232.
- [10] Z. Wu, S. Zhou, J. Li, X.P. Zhang, Real-Time Scheduling of Residential Appliances via Conditional Risk-at-Value, *IEEE Trans. Smart Grid.* 5 (2014) 1282–1291. doi:10.1109/TSG.2014.2304961.
- [11] R. Halvgaard, N.K. Poulsen, H. Madsen, J.B. Jørgensen, Economic Model Predictive Control for building climate control in a Smart Grid, in: 2012 IEEE PES Innov. Smart Grid Technol., 2012: pp. 1–6. doi:10.1109/ISGT.2012.6175631.
- [12] M. Ali, J. Jokisalo, K. Siren, M. Lehtonen, Combining the Demand Response of direct electric space heating and partial thermal storage using LP optimization, *Electr. Power Syst. Res.* 106 (2014) 160–167. doi:https://doi.org/10.1016/j.epsr.2013.08.017.
- [13] H.T. Nguyen, D. Nguyen, L.B. Le, Home energy management with generic thermal dynamics and user temperature preference, in: 2013 IEEE Int. Conf. Smart Grid Commun., 2013: pp. 552–557. doi:10.1109/SmartGridComm.2013.6688016.
- [14] M. Ali, J. Jokisalo, K. Siren, A. Safdarian, M. Lehtonen, A User-centric Demand Response Framework for Residential Heating, Ventilation, and Air-conditioning Load Management, *Electr. Power Components Syst.* 44 (2016) 99–109. doi:10.1080/15325008.2015.1101726.
- [15] M. Ali, A. Safdarian, M. Lehtonen, Demand response potential of residential HVAC loads considering users preferences, in: IEEE PES Innov. Smart Grid Technol. Eur., 2014: pp. 1–6. doi:10.1109/ISGTEurope.2014.7028883.
- [16] A. Safdarian, M. Ali, M. Fotuhi-Firuzabad, M. Lehtonen, Domestic EWH and HVAC management in smart grids: Potential benefits and realization, *Electr. Power Syst. Res.* 134 (2016) 38–46. doi:https://doi.org/10.1016/j.epsr.2015.12.021.
- [17] D.T. Nguyen, L.B. Le, Optimal energy management for cooperative microgrids with renewable energy resources, in: 2013 IEEE Int. Conf. Smart Grid Commun., 2013: pp. 678–683. doi:10.1109/SmartGridComm.2013.6688037.
- [18] M.E. Khodayar, M. Barati, M. Shahidehpour, Integration of High Reliability Distribution System in Microgrid Operation, *IEEE Trans. Smart Grid.* 3 (2012) 1997–2006. doi:10.1109/TSG.2012.2213348.
- [19] M. Banaei, B. Rezaee, Fuzzy scheduling of a non-isolated micro-grid with renewable resources, *Renew. Energy.* 123 (2018) 67–78. doi:https://doi.org/10.1016/j.renene.2018.01.088.
- [20] S.Y. Derakhshandeh, A.S. Masoum, S. Deilami, M.A.S. Masoum, M.E. Hamedani Golshan, Coordination of Generation Scheduling with PEVs Charging in Industrial Microgrids, *IEEE Trans. Power Syst.* 28 (2013) 3451–3461. doi:10.1109/TPWRS.2013.2257184.
- [21] H.S.V.S.K. Nunna, S. Doolla, Demand Response in Smart Distribution System With Multiple Microgrids, *IEEE Trans. Smart Grid.* 3 (2012) 1641–1649. doi:10.1109/TSG.2012.2208658.
- [22] S. Mohammadi, S. Soleymani, B. Mozafari, Scenario-based stochastic operation management of MicroGrid including Wind, Photovoltaic, Micro-Turbine, Fuel Cell and Energy Storage Devices, *Int. J. Electr. Power Energy Syst.* 54 (2014) 525–535. doi:10.1016/j.ijepes.2013.08.004.
- [23] D.T. Nguyen, L.B. Le, Optimal Bidding Strategy for Microgrids Considering Renewable Energy and Building Thermal Dynamics, *IEEE Trans. Smart Grid.* 5 (2014) 1608–1620. doi:10.1109/TSG.2014.2313612.
- [24] T. Niknam, R. Azizipanah-Abarghooee, M.R. Narimani, An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation, *Appl. Energy.* 99 (2012) 455–470. doi:10.1016/j.apenergy.2012.04.017.
- [25] J. Silvente, G.M. Kopanos, E.N. Pistikopoulos, A. Espuña, A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids, *Appl. Energy.* 155 (2015) 485–501. doi:10.1016/j.apenergy.2015.05.090.
- [26] J. Silvente, G.M. Kopanos, E.N. Pistikopoulos, A. Espuña, Reactive Scheduling for the Coordination of Energy Supply and Demand Management in Microgrids, in: 2014: pp. 493–498. doi:10.1016/B978-0-444-63456-6.50083-1.
- [27] A. Parisio, E. Rikos, G. Tzamalīs, L. Glielmo, Use of model predictive control for experimental microgrid optimization, *Appl. Energy.* 115 (2014) 37–46. doi:10.1016/j.apenergy.2013.10.027.
- [28] J. Silvente, A.M. Aguirre, M.A. Zamarripa, C.A. Méndez, M. Graells, A. Espuña, Improved time representation model for the simultaneous energy supply and demand management in microgrids, *Energy.* 87 (2015) 615–627. doi:10.1016/j.energy.2015.05.028.
- [29] H. Shuai, J. Fang, X. Ai, Y. Tang, J. Wen, H. He, Stochastic Optimization of Economic Dispatch for Microgrid Based on Approximate Dynamic Programming, *IEEE Trans. Smart Grid.* (2018) 1–1. doi:10.1109/TSG.2018.2798039.
- [30] W.B. Powell, S. Meisel, Tutorial on Stochastic Optimization in Energy—Part II: An Energy Storage Illustration, *IEEE Trans. Power Syst.* 31 (2016) 1468–1475. doi:10.1109/TPWRS.2015.2424980.
- [31] <https://www.fortum.fi/kotiasiakkaille/sahkoa-kotiin/oman-tuotannon-myynti-lahisahko>
- [32] https://caruna-cms-prod.s3-eu-west-1.amazonaws.com/caruna_fed_network_service_fees_1.3.2017_en.pdf
- [33] <https://www.helensahkoverkko.fi/globalassets/hinnastot-ja-sopimusedot/hsv---enkku/distribution-tariffs.pdf>
- [34] www.nordpoolspot.com

- [35] P.S. Hale, R.G. Arno, S.J. Briggs, Operational maintenance data for power generation distribution and HVAC components, *IEEE Trans. Ind. Appl.* 35 (1999) 282–297. doi:10.1109/28.753619.
- [36] I. Dinwoodie, O.-E. V. Endrerud, M. Hofmann, R. Martin, I.B. Sperstad, Reference Cases for Verification of Operation and Maintenance Simulation Models for Offshore Wind Farms, *Wind Eng.* 39 (2015) 1–14. doi:10.1260/0309-524X.39.1.1.
- [37] S. Küfeoğlu, M. Lehtonen, Comparison of different models for estimating the residential sector customer interruption costs, *Electr. Power Syst. Res.* 122 (2015) 50–55. doi:https://doi.org/10.1016/j.epsr.2014.12.026.
- [38] A.D. Jones, C.P. Underwood, A modelling method for building-integrated photovoltaic power supply, *Build. Serv. Eng. Res. Technol.* 23 (2002) 167–177. doi:10.1191/0143624402bt040oa.
- [39] M. Ali, M. Humayun, M. Degefa, A. Alahäivälä, M. Lehtonen, A. Safdarian, A framework for activating residential HVAC demand response for wind generation balancing, *2015 IEEE Innov. Smart Grid Technol. - Asia (ISGT ASIA)*. (2015) 1–6. doi:10.1109/ISGT-Asia.2015.7387046.
- [40] F. Martín-Martínez, A. Sánchez-Miralles, M. Rivier, Prosumers' optimal DER investments and DR usage for thermal and electrical loads in isolated microgrids, *Electr. Power Syst. Res.* 140 (2016) 473–484. doi:10.1016/j.epsr.2016.05.028.
- [41] P. Bacher, H. Madsen, Identifying suitable models for the heat dynamics of buildings, *Energy Build.* 43 (2011) 1511–1522. doi:10.1016/j.enbuild.2011.02.005.
- [42] F. Amara, K. Agbossou, A. Cardenas, Y. Dubé, S. Kelouwani, Comparison and Simulation of Building Thermal Models for Effective Energy Management, *Smart Grid Renew. Energy.* 06 (2015) 95–112. doi:10.4236/sgre.2015.64009.
- [43] M. Ali, M.Z. Degefa, M. Humayun, A. Safdarian, M. Lehtonen, Increased Utilization of Wind Generation by Coordinating the Demand Response and Real-time Thermal Rating, *IEEE Trans. Power Syst.* 31 (2016) 3737–3746. doi:10.1109/TPWRS.2015.2498899.
- [44] A. Bashir, M. Pourakbari Kasmaei, A. Safdarian, M. Lehtonen, Matching of Local Load with On-Site PV Production in a Grid-Connected Residential Building, *Energies.* 11 (2018) 2409. doi:10.3390/en11092409.
- [45] M. Pourakbari-Kasmaei, M.J. Rider, J.R.S. Mantovani, An Unambiguous Distance-Based MIQP Model to Solve Economic Dispatch Problems with Disjoint Operating Zones, *Power Syst. IEEE Trans.* 31 (2016) 825–826. doi:10.1109/TPWRS.2015.2394317.
- [46] K. Ahmed, P. Pylsy, J. Kurnitski, Hourly Consumption Profiles of Domestic Hot Water for Finnish Apartment Buildings, (2016).
- [47] <http://en.ilmatieteenlaitos.fi/>
- [48] J. Ekström, M. Koivisto, I. Mellin, R.J. Millar, M. Lehtonen, A Statistical Model for Hourly Large-Scale Wind and Photovoltaic Generation in New Locations, *IEEE Trans. Sustain. Energy.* 8 (2017) 1383–1393. doi:10.1109/TSTE.2017.2682338.