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Authors(s)	Anwar, Muhammad Bashar, O'Malley, Mark, Burke, Daniel J.
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Optimal Charging Schedules for Thermal Electric Storage in the Absence of Communication

Muhammad Bashar Anwar , Mark O'Malley
Energy Institute, University College Dublin,
Dublin, Ireland
muhammad.anwar@ucdconnect.ie
mark.omalley@ucd.ie

Daniel J. Burke
Electrical Engineer,
Warwick, UK
dnlbrk157@gmail.com

***Abstract*—Thermal Electric Storage (TES) has emerged as a promising power-to-heat technology with the potential of enabling active Demand Side Management (DSM). Optimal exploitation of the DSM capability of TES devices requires two-way communication with the grid. However, several contingencies and/or limitations on communication capabilities would render these storage devices incapable of being of any service to the system. This study presents the development of optimal charging schedules for the distributed TES devices which would determine the operation of these devices in the absence of communication. Different strategies are proposed which determine optimal TES charging dependence on local parameters including time of the day, household power consumption and outside temperature. Performance of the proposed charging schedules is then compared to the optimal communication-enabled and the conventional night-time charging scenarios for the All-Island Power System (AIPS). The results demonstrate the superiority of the proposed strategies as compared to the conventional night-time charging in terms of significant reduction in annual generation costs and energy consumption. Additionally, charging based on the proposed strategies can achieve up to 43% of the total cost savings potential of the communication-enabled scenario.**

***Index Terms*—Demand-side management, Electric heating, Local control, Power generation dispatch, Thermal Storage.**

NOMENCLATURE

Constants

Δj	Time step (h)
η_n	Hourly energy retention parameter of TES space heater
κ_n	Number of houses for archetype n
$\pi_{g,i}$	Conventional generator operating cost (e/MWh)
D^j_{base}	Non-heating electricity base load (MW)
E^{max}_n	Maximum storage capability of TES space heater (MWh)
g^{max}_i	Conventional generator maximum power rating (MW)
g^{min}_i	Conventional generator minimum stable level(MW)
$H^{p,j}_n$	Household power consumption allocated to each segment (MW)
I	Number of conventional generators
J	Optimization time horizon
N	Number of archetypes
O^j_n	Binary indicator for active occupancy
Q^{max}_n	Maximum heat output capability of TES space heater(MWh)
S^{max}_n	Electric power rating of TES space heater(MW)
$snsp_{lim}$	System Non-Synchronous Penetration Limit
$T^{max}_{n,r}$	Maximum room temperature ($^{\circ}$C)
$T^{min}_{n,r}$	Minimum room temperature ($^{\circ}$C)
$T^{o,j}_{out,n}$	Outdoor temperature allocated to each segment ($^{\circ}$C)
W^j_{av}	Available wind power (MW)

Variables

α^p_{const}	Constant coefficient for HPCD
α^p_n	Segments' coefficients for HPCD
β^o_{const}	Constant coefficient for OTD
β^o_n	Segments' coefficients for OTD
E^j_n	Energy level of TES space heater in archetype n at time j (MWh)
g^j_i	Power output of generator i at time j (MW)
P^j_n	Space heating power consumption of archetype n at time j (MW)
Q^j_n	Active heat output of TES space heater in archetype n at time j (MWh)
$Q^j_{n,heat}$	Total heat input in archetype n at time j (MWh)
$Q^j_{n,loss}$	Storage heat losses of TES space heater in archetype n at time j (MWh)
$T^j_{n,r}$	Room temperature of archetype n at time j ($^{\circ}$C)
w^j	Total wind power output at time j (MW)

I. INTRODUCTION

Space and water heating demand contributes to approximately 80% of the final energy consumption in residential buildings in Europe [1]. Therefore, decarbonisation of the heating sector through electrification of residential heat supply is identified as a key priority in the transition towards future low-carbon systems [2]. Thermal Electric Storage (TES) for domestic heating has been attracting growing interest as a promising electricity-to-heat technology with the capability of participation in active DSM. TES space heaters contain a highly insulated solid thermal energy storage core which enables the conversion of electrical energy into thermal energy stored in an efficient manner for use at a later time and are equipped with communications and control architecture [3].

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These devices allow the decoupling of intra-day scheduling of electric power demand from the time of thermal energy end-use while satisfying the end-users' thermal comfort requirements.

Many studies have shown that these devices can facilitate load shifting and energy arbitrage [4]–[6]. However, all these studies above assume the TES devices are equipped with two-way communication capabilities. However, this essential assumption might not hold in practice for several reasons. According to [7], many smart grid projects have reported that telecommunications issues have arisen which have affected deployment at project level, and would potentially be even more serious at roll-out on a larger scale. These issues are caused by either the absence of communication capabilities, the cost of communication infrastructure and/or the need to accommodate a very large volume of communicated data. Additionally, other issues related to the communications requirement including security, privacy and reliability concerns have been well documented [8]. Considering the fact that most communication systems can not guarantee continuous operation, [9] recommends the need of a "fail-safe" operation mode for control of appliances without communication requirements.

Several local control strategies for achieving various objectives using Electric Vehicles (EVs) have been presented in literature. In [10], the authors propose a vehicle-to-grid model for provision of primary reserve without system-wide information exchange while satisfying the scheduled charging by the user based on droop characteristics against measured frequency deviations. Comparison of two classes of EV charging coordination schemes (local vs. global) is presented in [11], where the objective of both the approaches is to reduce the peak load and load variability in a distribution network. The global optimization problem outperforms the local optimization in terms of optimality however, the local algorithm requires minimum communication and is also scalable and flexible. Similarly, decentralized control strategies for Thermostatically Controlled Loads (TCLs) have been presented in [12], [13]. In [12], the authors propose a randomized priority control strategy for controlling a collection of TCLs for tracking a regulation service signal. The proposed control scheme reduces the communications requirement and facilitates practical implementation. Local control strategies based on randomized controllers using the mean-field load model are described in [13]. The proposed control strategies allows individual loads to take decisions based on the centrally broadcasted demand dispatch signal and its own Quality of Service (QoS) and other local state variables. The aforementioned local strategies have shown to significantly reduce the communications requirement associated to direct load control, however, these strategies still are dependent on a centrally broadcasted reference signal and thus can not govern power consumption in the absence of any communication. Local strategies based on 'fit-and-forget' type of settings for reactive power control of distributed generation in the absence of communication capabilities have been reported [14], [15]. These strategies define the reactive power output for the individual generators as a function of local voltage measurements, thereby achieving reactive power control without the need for a centrally broadcasted signal. However, none of the studies have looked into the development of settings for flexible domestic appliances (including thermal loads) which would determine the operation of these devices in the absence of communication.

This paper presents novel optimal charging strategies for residential TES space heating devices using an integrated Building-to-Grid (B2G) model. Similar to night-time charging, the presented strategies determine default 'fit-and-forget' type of charging schedules to be followed in the absence of communication for different months of the year. It is assumed that the devices have access to local information and subsequently, four strategies based on different local parameters which can affect the charging pattern of TES loads including time of the day, household power consumption and outside temperature have been discussed. Having monthly schedules allows the consideration of several scenarios which can manifest during the month, thereby resulting in robust charging schedules. Additionally, the magnitude of space heating requirements have relatively small variations across a month, therefore it is sensible to have the same schedule for the whole month. The same general strategies can be applied for domestic hot water storage loads as well. The proposed strategies are compared to two reference scenarios: a centralised daily scheduling of the TES devices based on two-way communication with the grid; and a night-time charging scheme which is the conventional mode of operation of TES devices in the absence of communication. The performance of the strategies is evaluated in terms of annual generation cost savings and reduction in energy consumption based on implementation on the All-Island Power System (AIPS) model.

The rest of the paper is organized as follows. Section II presents the modelling details and methodology for the development of the B2G model. Section III discusses the proposed charging strategies and the reference scenarios. Section IV presents the results and performance of proposed schemes in comparison to the reference scenarios. And finally, Section V concludes the findings of this study.

II. Building-to-Grid Model

The Building-to-Grid (B2G) model forms the framework for the determination of the charging schedules for the TES devices. It is fundamentally an economic dispatch model, which minimises total cost of electricity generation, subject to system operational constraints, technical constraints of the generating units and thermal demand constraints of the considered dwellings. Integration of the building thermal dynamics with the power system economic dispatch models facilitates the co-optimisation of generation scheduling with TES charging while satisfying end-user thermal comfort requirements. Three different midflat archetypes based on different periods and materials of construction are considered in this study. The archetypes are modelled using the thermal network topology state space model as discussed in detail in [16]. The space heating demands determined using the three archetypes are then scaled up (using a scaling factor, κ_n) to represent the stock of electrically heated midflats in Ireland. The B2G model optimisation problem is formulated as follows:

$$min \sum_{j=1}^{J} \sum_{i=1}^{I} (\pi_{g,i}.g_i^j) \quad (1)$$

subject to:

$$\sum_{i=1}^{I} g_i^j + w^j = \sum_{n=1}^{N} (\kappa_n.P_n^j) + D_{base}^j, \quad \forall j \in [1, J] \quad (2)$$

$$w^j \leq snsp_{lim}. \left(\sum_{n=1}^{N} (\kappa_n.P_n^j) + D_{base}^j \right), \quad \forall j \in [1, J] \quad (3)$$

$$T_{n,r}^{min}.O_n^j \leq T_{n,r}^j.O_n^j \leq T_{n,r}^{max}.O_n^j, \quad \forall j \in [1, J] \quad \forall n \in [1, N] \quad (4)$$

$$E_n^{j+1} = E_n^j + P_n^j.\Delta j - Q_n^j - Q_{n,loss}^j, \quad \forall j \in [1, J] \quad \forall n \in [1, N] \quad (5)$$

$$Q_{n,loss}^j = (1 - \eta_n).E_n^j, \quad \forall j \in [1, J] \quad \forall n \in [1, N] \quad (6)$$

$$Q_{n,heat}^j = Q_n^j + Q_{n,loss}^j, \quad \forall j \in [1, J] \quad \forall n \in [1, N] \quad (7)$$

$$0 \leq Q_n^j \leq Q_n^{max}, \quad \forall j \in [1, J] \quad \forall n \in [1, N] \quad (8)$$

$$0 \leq P_n^j \leq P_n^{rat}, \quad \forall j \in [1, J] \quad \forall n \in [1, N] \quad (9)$$

$$0 \leq E_n^j \leq E_n^{max}, \quad \forall j \in [1, J] \quad \forall n \in [1, N] \quad (10)$$

The objective function (1) of the B2G model minimises the cost of electricity generation, which is the summation of conventional generation costs ($\pi_{g,i}.g_i^j$). The cost of conventional generation ($\pi_{g,i}$) takes into account the fuel and carbon emissions costs. Eqs. (2) and (3) represent the power system operational constraints. The power balance constraint is formulated in (2), which ensures that the total electricity generation equals the total demand at all times. The total electricity demand is represented as the sum of the fixed baseline demand (D_{base}^j) (excluding the heating load for the considered archetypes) and the flexible heating demand ($\kappa_n.P_n^j$). Eq. (3) constrains the wind generation (w^j) to be within the System Non-Synchronous Penetration (SNSP) limit, which is defined as the ratio of non-synchronous generation to demand [17]. The thermal comfort constraint (4), ensures the room temperature, ($T_{n,r}^j$) to be within the thermal comfort limits during active occupancy periods (O_n^j). $T_{n,r}^j$ is determined using the state space model as described in [16]. The evolution of the storage level (E_n^j) of the TES for space heating in terms of the storage level after the previous hour (E_n^{j-1}), charging power consumption (P_n^j), active heat output (Q_n^j) and the storage heat losses is modeled in (5). TES space heating storage losses are calculated using (6). The total space heating input ($Q_{n,heat}^j$) is descibed as the summation of active heat output of the TES and the storage heat losses in (7). Eqs. (8)-(10) constrain the active heat output, charging power and storage level of the TES space heaters to be within their respective rated values. The technical constraints for the generating units (including minimum and maximum limits, ramping constraints and wind availability constraint) are also considered, which can be referred to in [16].

III. TES Charging Strategies

A. Proposed Charging Schemes

The optimal communication-less charging profiles are determined by solving the B2G model with an hourly resolution using a monthly look-ahead horizon ($J = number\ of\ days\ in\ each\ month * 24$). Using a monthly horizon facilitates the formulation of TES charging dependence on local building-level parameters including time, household power consumption and outdoor temperature for every month of the year. These monthly profiles could then be programmed into the individual appliances at the time of installation as fit-and-forget settings to be followed in the absence of communication.

1) Time Dependent Strategy: Similar to night-time charging, the default charging profile of TES devices can be made time dependent. However, in contrast to the fixed schedules used in night time charging, the time dependent (TD) strategy determines the optimal timing and magnitude of charging schedules for each month. The optimal dependence of TES charging on the hour of the day is determined by adding the following constraint in the B2G model:

$$P_n^j = P_n^{j+24} \quad \forall n \in [1, N] \quad \forall j \in [1, J - 24] \quad (11)$$

The constraint expressed in (11) ensures that the charging power consumption (P_n^j) for the TES devices for a particular hour of the day is the same for the whole month. Therefore, the schedules for each hour of the day which minimise the monthly generation costs can be obtained.

2) Household Power Consumption Dependent Strategy: The household power consumption dependent (HPCD) strategy determines the dependence of TES charging on the power consumption of the house (excluding heating requirement), which is available without communication requirements. In the absence of communication, it could argued that power consumption of each house could be taken as a proxy for system demand and therefore a TES charging strategy dependent on household power consumption might be more representative of the system operation. Additionally, such a strategy can be adopted to constrain the peak electricity demand of each household. To obtain the HPCD schedules, the B2G model is solved for the whole month with the following additional constraint:

$$P_n^j = \alpha_n^{const} + \sum_{p}^{NP} \left(\alpha_n^p H_n^{p,j} \right) \ \forall n \in [1, N] \ \forall j \in [1, J] \quad (12)$$

In order to keep the optimisation problem linear while allowing for a non-linear dependence of TES charging on household power consumption, the range of household power consumption for each month is first divided in to NP equal segments. The power consumption for each hour of the month is then allocated to the segments ($H_n^{p,j}$). Subsequently, (12) allows the determination of the optimal coefficients (α_n^p) for each power segment and a constant α_n^{const}, resulting in a piece-wise linear dependence of TES charging power consumption on the household power consumption.

3) Outdoor Temperature Dependent Strategy: Outdoor temperatures have a significant impact on the heating requirements for each dwelling and, therefore, are vital for the determination of TES charging schedules. The outdoor temperature dependent (OTD) strategy determines the charging power consumption as a function of the outdoor temperature measurements for each household. This is implemented by including the following constraint in the B2G model:

$$P_n^j = \beta_n^{const} + \sum_o^{NO} \left(\beta_n^o T_{out,n}^{o,j} \right) \; \forall n \in [1, N] \; \forall j \in [1, J] \quad (13)$$

As implemented in HPCD, the range of the outdoor temperatures is first divided in to NO equal segments. The outdoor temperature for each hour of the month is then allocated to the segments ($T_{out,n}^{p,j}$). Subsequently, the constraint expressed in (13) is used to determine the optimal coefficients (β_n^o) for each segment and a constant β_n^{const}, resulting in a piece-wise linear dependence of TES charging power consumption on the external temperature.

4) Combined Dependence Strategy: The combined dependence (CD) strategy determines the monthly TES charging schedules dependent on both the household power consumption and outdoor temperature. Such a combined dependence profile could help exploit the representativeness of both the aforementioned HPCD and OTD strategies, thereby, resulting in a better cost saving performance in the absence of any communication. Similar to the HPCD and OTD strategies, the household power consumption and outdoor temperature range is divided into segments and the optimal coefficients for each month are determined by adding the following constraint to the B2G model:

$$P_n^j = \gamma_n^{const} + \sum_p^{NP} \left(\alpha_n^p H_n^{p,j} \right) + \sum_o^{NO} \left(\beta_n^o T_{out,n}^{o,j} \right) \quad (14)$$
$$\forall n \in [1, N] \quad \forall j \in [1, J]$$

The formulation presented above enables the representation of TES charging power consumption as a two-dimensional piece-wise linear function of household power and external temperature for each month.

B. Reference Scenarios

1) Daily Charging Optimisation: The centralised daily charging optimisation scenario assumes two-way communication capabilities for the TES devices. To implement this framework, the B2G model is solved with an hourly resolution and a look-ahead horizon of 48 hours. The results for the first 24 of those 48 hours are stored, before rolling on to the next day of the year. The charging instructions are then dispatched to the TES loads. This rolling-optimisation approach allows the B2G to consider keeping some storage in the TES at the end of the day depending on the conditions the next day.

2) Conventional Night Time Charging: Load shifting capability of thermal electric storage has conventionally been achieved by implementation of night time charging in order to exploit the off-peak tariffs. For the night time charging scheme, all the TES devices are assumed to charge at rated power from 00:00 to 07:00 until they are fully charged or until the night period ends [18]. This scheme is implemented by first calculating the night charging schedules for the next day and then treating these schedules as a fixed demand in the B2G model for the next day.

IV. Results and Discussion

The developed B2G model has been used to conduct an annual comparison of the proposed strategies for the AIPS. The conventional generation portfolio of the AIPS, including the number of units, heat rates and other important characteristics have been modelled according to [19]. The associated fuel costs of the various fuels for the year 2012 are obtained from [20] and the fuel carbon intensities are based on [21]. The modelling assumptions, number of midflats and characteristics of the TES devices are detailed in [16].

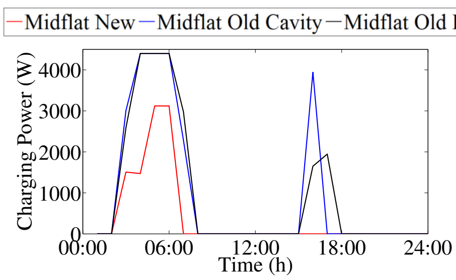
The TD charging schedules established for the months of February and March are depicted in Fig. 1 for all 3 archetypes. It can be observed that the charging times are distributed in two sessions: one during late night and the other just before the evening heating requirement. This implies that night time charging is not the most effective charging scheme for TES loads in terms of generation cost reduction for these months. It can also be noticed from the areas under the curves that the energy consumed in February are greater than that in March. This is because February tends to be colder than March, resulting in larger heating requirements. This validates the rationale of using different schedules for each month. Additionally, the heating requirements for the new midflat are significantly lower owing to a better insulated building fabric as compared to the older midflats.

The HPCD charging schedules for new midflats based on different numbers of segments for February are presented in Fig. 2. It can be observed that keeping a single segment results in a droop-like profile for HPCD schedules. This would mean that the TES devices will continue charging at low power levels throughout the whole day. Increasing the number of segments increases the flexibility for determining the charging schedules. For example, if 15 segments are considered, the charging power levels are high for specific household power consumption levels and 0 for the rest of the segments. Fig. 3 shows the OTD schedules for new midflats for the month of February. As explained earlier, including more segments results in a more complicated piece-wise relationship of charging power and outdoor temperature. A general trend however can be noticed. Charging power consumptions tend to be high for values of temperature less than 3 °C and between 8-10 °C. This can be attributed to the outdoor temperature generally being lower than 3°C during the nights and between 8-10 °C near the evening heating requirement for February. The impact of having different numbers of segments on the annual generation costs is shown in Fig. 4. It can be noticed that charging schedules based on OTD result in lower annual generation costs as compared to HPCD schedules. Additionally, it can be observed that increasing the number of segments results in better performance however, there is a saturating effect as the numbers of segments is increased above 15. It must also be taken into account that larger number of segments makes the optimisation problem computationally expensive. Therefore, 15 segments for both OTD and HPCD are considered for the rest of the analysis.

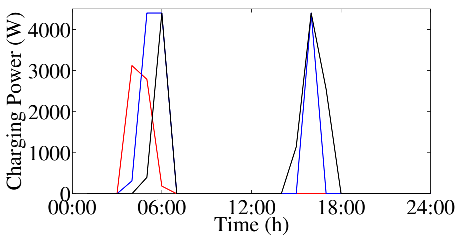
The CD profile for February for new midflats is depicted in Fig. 5. It can be observed that charging the TES devices based on the combined dependence allows greater flexibility in terms of increased combinations which would result in a more effective and robust modulation of TES charging.

The reduction in monthly generation costs for the proposed strategies as compared to the night time charging is presented in Fig.6. It can be observed that the CD strategy outperforms the others with the TD strategy being the least efficient for all the months. There are no differences in costs for the months Jun-Aug as there is no space heating requirement for this period. Interestingly, OTD control performs better for some of the months as compared to HPCD, while HPCD performs better in others. Therefore, by combining the benefits of both these strategies, CD profiles result in lower generation costs throughout the year.

Fig. 7 depicts the annual performance of the proposed local strategies compared to the night time and centralised control schemes. It can be observed from Fig. 7a that all the proposed local strategies perform better than the conventional night time charging scheme for TES devices, which highlights the effectiveness of the proposed strategies. Among the local strategies, CD leads to the lowest annual costs, followed by OTD, HPCD and TD. The communication-enabled cen-



(a) Charging schedules for February.



(b) Charging schedules for March.

Fig. 1. Time dependent charging schedules.

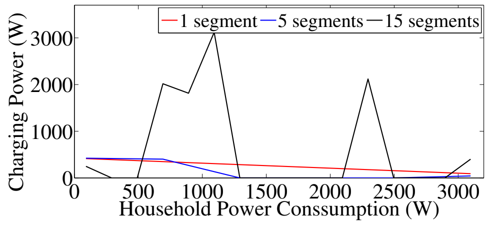


Fig. 2. HPCD charging schedules for new midflats.

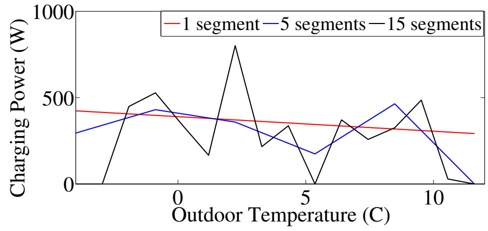


Fig. 3. OTD charging schedules for new midflats.

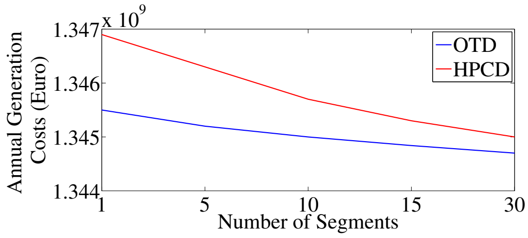


Fig. 4. Annual costs for different number of segments.

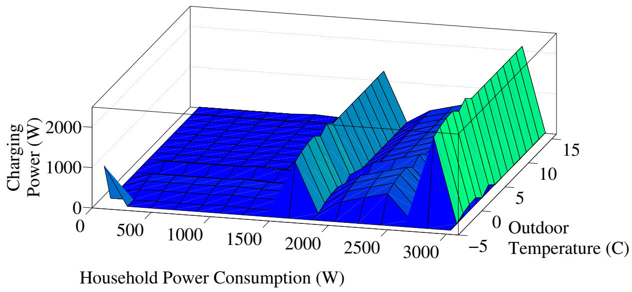


Fig. 5. CD charging schedules for new midflats.

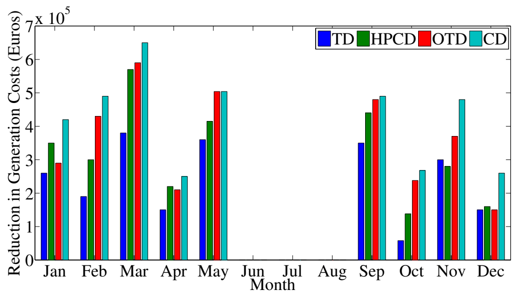
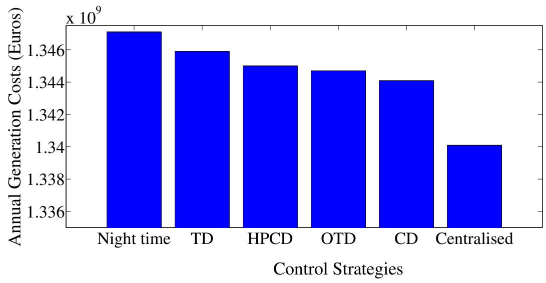
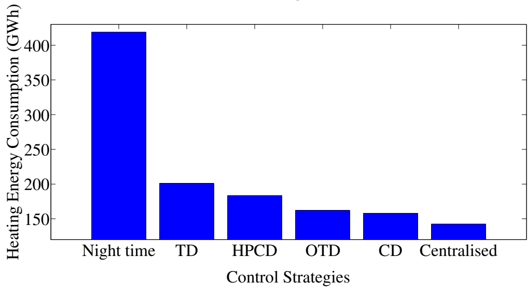


Fig. 6. Monthly Comparison of Local Strategies.



(a) Annual generation costs.



(b) Annual heating demand.

Fig. 7. Annual performance of control strategies.

tralised control outperforms all the local strategies with a cost reduction of circa €7 million as compared to night time charging. However, it must be noted that CD can enable a cost reduction of circa €3 million compared to night time charging, thereby achieving 43% of the cost savings obtained through the centralised control. These differences in costs are a result of not only shifting the load to lower cost periods but also due to reduction in energy consumption as depicted in Fig. 7b. The night time charging scheme requires significantly more energy as the TES devices are charged to the maximum storage levels every day irrespective of the heating requirements, resulting in significant wastage of energy. As the proposed local strategies optimise the charging power based on local variables and the heating requirements, the annual energy consumption values are comparable to that of centralised control. Therefore, it can be concluded that proposed strategies are significantly superior to the conventional practice of charging the TES devices at night.

V. Conclusions

This paper presents the development of local control strategies which would determine the charging schedules of TES devices in the absence of communication capabilities. The B2G model forms the framework for determination of monthly schedules for 4 different local strategies based on time of the day, household power consumption and outdoor temperatures. The performance of the proposed strategies is then compared to the optimal communication-enabled and the conventional night-time charging scenarios for the AIPS. The results demonstrate the superiority of the proposed strategies as compared to the conventional night-time charging in terms of significant reduction in annual generation costs and energy consumption. Additionally, the local strategies can achieve up to 43% of the total cost savings potential of the centralised scenario.

Future work will evaluate the robustness of the determined schedules by implementation on a more detailed Unit Commitment model for different years of data. Additionally, the proposed local strategies can be extended to incorporate other residential archetypes, load types and different occupancy patterns.

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