ENERGY MANAGEMENT OPTIMIZATION IN CAMP IT INFRASTRUCTURE BASED ON A DEMAND RESPONSE PERSPECTIVE

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SUMMARY: Demand response (DR) offers the path for consumers to change their normal energy consumption patterns in response to significant variations in energy pricing over time. An effective and wide scale implementation of DR may lead to lower energy demand during peak hours and minimize energy associated costs and outages. DR can be more cost-effective than adding generation capabilities to meet the peak or occasional demand spikes. The underlying objective for an effective wide implementation of DR is to actively engage users in modifying their consumption. Also, DR is expected to increase energy market efficiency, transparency and security of supply in the future which will ultimately lead to significantly lower environmental impact.This paper demonstrates a demand response optimization frameworkand some initial resultsfor the Camp IT infrastructure at Technical University of Crete.

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1 INTRODUCTION

EU has developed an initial legislative framework for Demand Response (DR) with the Electricity Directive (2009/72/EC), the Energy Efficiency Directive (2012/27/EU) and the Network Codes. To increase shareholder engagement in demand response the Energy Efficiency Directive is calling on Member States to remove barriers in transmission and distribution putting demand response participation at risk. Main barriers that need to be overcome before we can expect to see the wide-scale implementation of demand response solutions are [1]:

- Absence of transparent, efficient and commercially attractive regulatory framework for the role of key stakeholders in the energy markets including demand aggregator business models.
- Lack of consumer trust and resistance to participating in demand response schemes.
- Deployment of smart meters and smart applications for engaging various categories of power consumers.
- Economic barriers related to the need for leveraging investments in the technical upgrade of power and communications infrastructure of the utilities, distribution network, microgrids, buildings, etc. in order to allow full exploitation demand response capabilities.

In order to overcome the aforementioned barriers existing efforts and successful projects should be put in a completely different perspective. Smart metering with IP connectivity have been already successfully exploited in previous projects such as Green@Hospital (www.greenhospital-project.eu) and ICE-WISH [2]. Already developed Web based Energy Management & Control Systems (EMCS) for hospitals should be further exploited in other sectors. Expert systems and control algorithms for energy load prediction and shaping in small communities are ready to be integrated in the future energy grids [3], [4]. Preliminary aggregator algorithms with real time energy management systems have been defined and tested within controlled lab tests [5], [6].

All the above are supported by the evolution of smart grids which through the incorporation of innovative Information and Computer technologies (ICT) will allow for two-way communication between utilities and customers/users. It is evident that the electrical power grids are being transformed to become more efficient and resilient — therefore, “smarter” — than the conventional power grids. The smartness is focused not only on elimination of black-outs, but also on making the grid greener, more efficient, adaptable to customers’ needs, and therefore less costly [1], [7].

Smart Grids open the door to new applications with far-reaching inter-disciplinary impacts: providing the capacity to safely integrate more renewable energy sources (RES), smart buildings and distributed generators into the network; delivering power more efficiently and reliably through demand response, comprehensive control and monitoring capabilities; enabling consumers to have greater control over their electricity consumption and to actively participate in the electricity market.

Smart grids entail a more pervasive technology that influences the daily life of users. Although users have not been actively involved in previous grid innovations, the role of users in the future energy system is critical[8]. Smart meters, intelligent platforms and software apps will provide the basis for the information exchange that will enable various categories of electricity consumers become also producers, so called prosumers, effectively managing their own energy production and consumption.

1.1 STATE OF THE ART

Various methodologies have been applied to investigate the potential application of demand response in different countries, customers and environments. As the literature in this field is rapidly expanding in breadth and depth an extensive review is out of the scope of this work. However a

brief description of a limited number of distinct related publications is provided as a hint of the advances related to the specific area of interest.
Bartusch et al [9] investigated the potential of residential demand response programs in Swedish family homes based on a time-of-use electricity distribution tariff. The implemented approach involved a model of the absolute and relative change in electricity consumption, shift in adjusted electricity consumption and maximum demand between peak and off-peak hours, relative change in the shape of demand curves representing weekdays and weekends and diversified demand. The study uses various metrics to evaluate demand response and differentiate results between single-family homes, condominium apartments and rental apartments. The results indicated significant reductions in demand at times of stress for the local power grid and variations between the home categories assessed related to uneven communication efforts engaging residents in DR.
Motegi et al [10] published a framework for DR strategies that have been tested in commercial buildings. Strategies and techniques emphasise in HVAC for air-conditioning and ventilation but also include lighting systems, miscellaneous equipment and non-component specific control. HVAC strategies such as global temperature adjustment and systemic adjustments to air distribution / cooling systems etc. are thoroughly presented based on system applicability, DR approach, sequence of operation, energy saving potential, rebound strategies, cautions and applied sites.
Park et al [11] proposed a model of self-organizing map (unsupervised learning feedforward neural network) and K-means clustering data mining techniques for customer baseline load estimation in demand response management aimed at quantifying demand reduction and verifying performance. Lower error rates were demonstrated compared to various day matching techniques by exploiting residential consumption of three cities.
Bartholomew et al [12] performed a comparison of the various methodologies concerning the impact evaluation and verification of demand response. Baseline methodologies such as day matching, previous days approach, average daily energy usage approach, proxy day approach, adjustment and regression methods have been explored. Authors argue that such techniques can provide baseline load curves valuable in evaluating and verifying hypothetical loads in the absence of a DR event.
Coughlin et al [13] applied various baseline load profiles to a sample of buildings to test their accuracy for evaluating load reductions in different DR schemes. Averaging and explicit weather models were exploited. A key finding in this study was that a morning adjustment factor could improve verification performance in weather sensitive commercial and institutional buildings. In addition it is demonstrated that for buildings with low variability most BLP models perform reasonably well. In contrast it is argued that buildings with high variable loads are difficult to characterise and therefore applying generic BLP models in such cases may not provide satisfactory results. Instead it is proposed that such customers may be given the option to enrol in a DR contract establishing a guaranteed load drop or reduction to a given firm service level.
Addy et al [14] analysed the effect of different modelling aspects on shed estimates. Weather data source, resolution of data, methods for determining building occupancy, alignment of building power data with temperature and power outage filtering were assessed. Shed estimates have been found to be particularly sensitive to outdoor air temperature data and therefore any baseline analysis is highly dependent on the availability of high quality weather data. In addition it was observed that predictions are sensitive on data filtering to flag and remove marginal data and therefore this is considered an essential step to avoid discrepancies. Another important outcome of this analysis is that shed estimates are not sensitive to building demand resolution up to one hour.
Panapakidis et al [15] proposed a methodology for pattern recognition of electricity load curve analysis of buildings using clustering techniques utilising a university campus as case study.

In this paper a initial demand response approach is developed and presented to highlight the potential benefits of energy and HVAC management from a different angle. Developing and implementing energy management techniques from a demand response perspective provides the basis for realistically addressing energy cost savings. For the aims of this study, a validated model of K1 building at the Technical University of Crete based on indoor and outdoor measurements was used. Minimization of the annual total cost of energy is exploited as the major criterion of the optimization. Modelling the cost of energy involved an analysis of the various cost domains:

- Energy consumption tariffs
- Maximum Power demand
- Power quality
- Transmission of energy
- Distribution of energy
- CO_2 rights
- Specific tax for emissions reduction
- Services of general interest
- Other costs

The cost of energy profile has been modelled according to the actual energy pricing profile obtained by the specific medium voltage pricing scheme for the Technical University of Crete campus. Energy cost data for the year 2015 was exploited for validation purposes.

2 METHODOLOGY

As basic input in this work, the validated thermal model in Open Studio / Energy Plus of K1 building of the campus in Technical University of Crete (fig.1) which was created in the framework of the Camp IT project (www.campit.gr), was exploited.

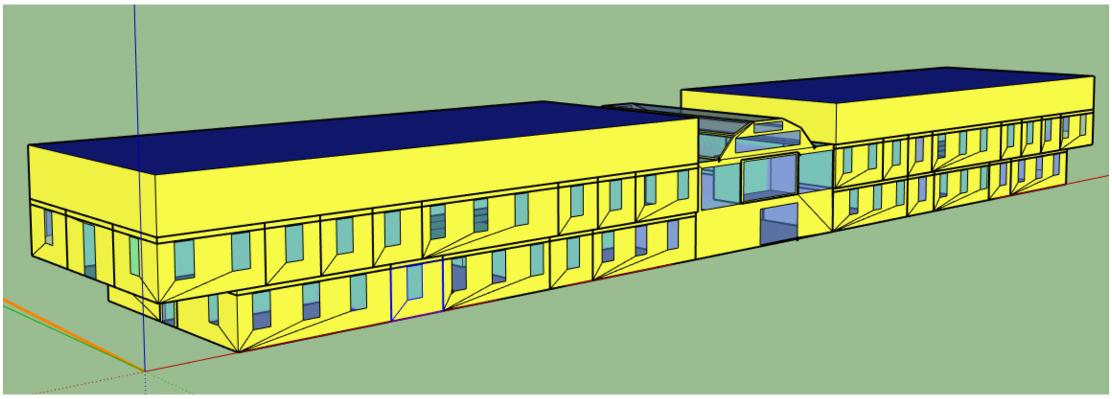

Fig. 1K1 building 3D thermal model

Matlab was used to import data concerning power loads from Energy Plus and perform the necessary transformations and calculations for obtaining energy and power related costs. Validating the energy cost model was implemented using the energy bills issued by HEDNO SA for the university campus during the whole of 2015. The model of energy cost was adjusted to keep certain factors constant as they depend on externalities i.e. energy market operations the volatility of which are out of the scope in this work.

2.1 Energy cost model: Input variables

For the purposes of this study the following variables were used as inputs to the energy cost model:

- Monthly energy consumption between 07:00-23:00 in working days during the year (E_A, kWh)
- Monthly energy consumption between 23:00-07:00 in working days, weekends and official holidays (E_B, kWh)

- Maximum Monthly Power Demand (P_{pk}, kW)

2.2 Energy Cost model: Objective function

The objective function of the energy cost model is given by eq.1:

$$[min]g(E,P) = C_{E,t} \quad (1)$$

The total cost of energy, $C_{E,t}$ is given by eq.2:

$$C_{E,t} = C_{E,P\_cns} + C_{adj} + C_{tax} \quad (2)$$

C_{E,P_cns}, C_{adj} and C_{tax} are further calculated by eq. 3, 4 and 5 respectively:

$$C_{E,P\_cns} = C_{E\_cns} + C_{P\_cns} + C_{CO2} \quad (3)$$

$$C_{adj} = C_{P\_tr} + C_{E\_dstr} + C_{g\_int} + C_{em} + C_{oth} \quad (4)$$

$$C_{tax} = C_{SCT} + C_{5‰} + C_{VAT} \quad (5)$$

The terms in eq.3 namely the cost of energy consumption C_{E_cns}, the cost of power demand C_{P_cns} and the cost of CO_2 rights, C_{CO2} are further specialised in equations 3.1, 3.2 and 3.3 respectively:

$$C_{E\_cns} = E_A C_{E_A} + E_B C_{E_B} \quad (3.1)$$

$$C_{P\_cns} = C_{u\_P\_ch} P_{pk} \quad (3.2)$$

$$C_{CO_2} = C_{u\_CO2\_ch}(E_A + E_B) \quad (3.3)$$

Similarly terms in eq.4 and in specific the cost of transmitted power C_{P_tr}, the cost of energy distributed C_{E_dstr}, the cost for general interest services C_{gen_int}, the cost of the Specific Tax for the Reduction of Air Emissions (STRAE) C_{strae} and the cost for Other services $C_{oth}$are given by equations 4.1-4.5:

$$C_{P\_tr} = C_{u\_P\_tr\_ch} P_{pk} \quad (4.1)$$

$$C_{E\_dstr} = C_{u\_dstr\_ch}(E_A + E_B) \quad (4.2)$$

$$C_{g\_int} = C_{u\_g\_int\_ch}(E_A + E_B) \quad (4.3)$$

$$C_{strae} = C_{u\_strae\_ch}(E_A + E_B) \quad (4.4)$$

$$C_{oth} = C_{u\_oth\_ch}(E_A + E_B) \quad (4.5)$$

Terms in equation 5 such as the Specific Consumption Tax (SCT) C_{SCT}, 5‰ Tax $C_{5‰}$and the cost of VAT C_{VAT} are provided by equations 5.1-5.3:

$$C_{SCT} = C_{u\_SCT\_ch}(E_A + E_B) \quad (5.1)$$

$$C_{5‰} = 0.005((C_{E,P_{cns}} + C_{adj}) - C_{STRAE} + C_{SCT})) \quad (5.2)$$

$$C_{VAT} = 0.13(C_{E,P_{cns}} + C_{adj} + C_{SCT}) \quad (5.3)$$

The model of energy cost was adjusted to keep certain factors constant as their variationsmostly depend on externalities which are not taken into account in the framework of this work. Such factors are:

- Power charge rate equal to 7.1 €/kW (value of 7.1 €/kW and 6 €/kW in the period of study)
- Emissions charge rate equal to 0.00478€/kWh (value of 0.00478 €/kWh and 0.00595€/kWh in the period of study)
- Variable energy charge rate equal to 0.002873€/kWh (value between 0.0028383 and 0.0028995)
- cosφ equal to 0.99 (value between 0.99-0.999)
- Specific Tax for Reduction of Carbon Emissions per unit of energy equal to 0.01277€/kWh (value of 0.01230€/kWh and 0.01277€/kWh in the period of study)

C_{E,P_cns}: Monthly cost of energy consumption and maximum power demand C_{adj} : Monthly cost for adjustable charges C_{tax} : Monthly cost of various taxes C_{E_cns} : Monthly cost of energy consumption according to the different tarrifs C_{P_cns} : Monthly cost of maximum power demand C_{CO2} : Monthly cost of CO_2 emissions C_{P_tr} : Monthly cost of transmission of power C_{E_dstr} : Monthly cost of energy distribution C_{g_int} : Monthly cost of general interest services C_{em} : Monthly fare linked with investments in Renewable Energy technologies for the reduction of emissions C_{oth} : Other monthly costs C_{SCT} : Specific Consumption Tax $C_{5‰}$: Monthly Tax C_{VAT} : Monthly VAT cost E_A: Monthly energy consumption between 7:00-23:00 in working days during the year in kWh E_B: Monthly energy consumption between 23:00-07:00 in working days, weekends and official holidays in kWh	C_{E_A} : Unit energy charge rate for consumption between 7:00-23:00 in working days during the year (equal to 0.06428 €/kWh) C_{E_B} : Unit energy charge rate for consumption between 23:00-07:00 in working days, weekends and official holidays (equal to 0.05062 €/kWh) $C_{u\_CO2\_ch}$: Unit charge for CO_2 emissions per kWh in €/kWh $C_{u\_P\_tr\_ch}$: Unit cost for the transmission of power per kW in €/kW P_{pk} : Monthly maximum power demand in kW $C_{u\_dstr\_ch}$: Unit cost for the distribution of energy per kWh in €/kWh $C_{u\_g\_int\_ch}$: Unit cost for the general interest services per kWh in €/kWh $C_{u\_strae\_ch}$: Unit cost for STRAE per kWh in €/kWh $C_{u\_oth\_ch}$: Unit cost for the other costs per kWh in €/kWh $C_{u\_SCT\_ch}$: Unit cost for the SCT per kWh in €/kWh

3 EXPERIMENTAL ANALYSIS

The experimental analysis involved different scenarios for preheating and precooling and comparison of energy costs in each case. This step required adding a HVAC system in the building model as shown in fig. 2:

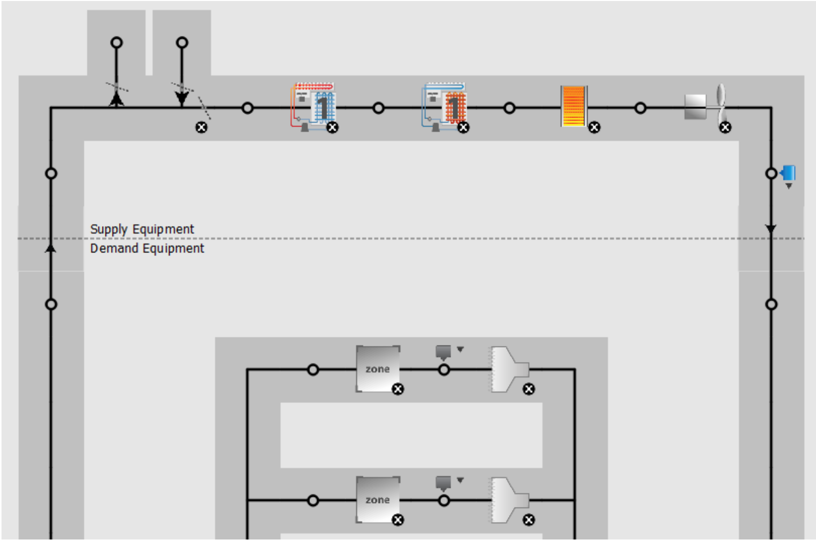

Figure 2: HVAC configuration in Open Studio.

Default values for Coefficient of Performance (COP) equal to 3 for heating and 5 for cooling were used. For the baseline scenario the operation of the HVAC systemwas set according to the heating and cooling schedules shown in fig. 3. In broad terms the baseline schedule is definedas a set point for the HVAC in heating mode of 20°Cand 25°C in cooling mode during typical working days and hours08:00-16:00 (weekends excluded).

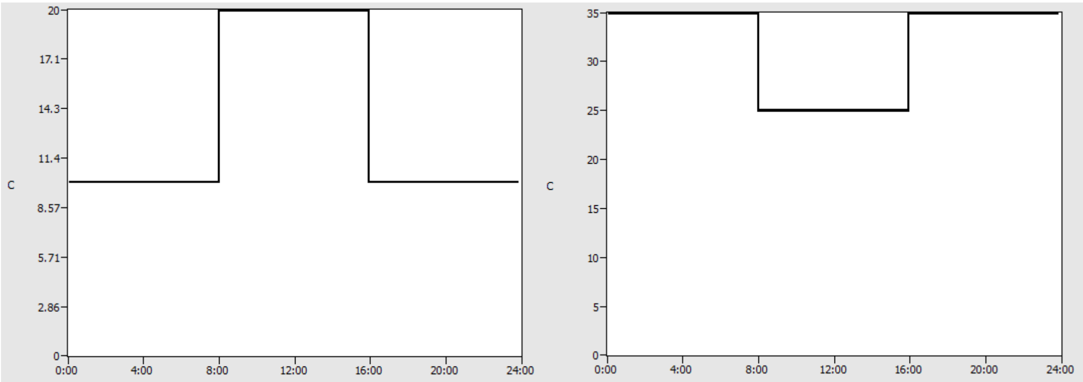

Figure 3: Heating (left)/ Cooling (right) schedule for HVAC system in baseline scenario.

For the preheating and precooling scenariosvarious different settings were tested. In figure 4one of the best performing preheating / precooling scenarioispresented in terms of the associated HVAC schedules. It is noted that the same set points as in the case of the baseline scenario for heating (20°C) and cooling (25°C) were applied but the heating and cooling timeframe within working days has been extendedto start earlier in the morning for both heating and cooling to take advantage of the low cost tariff between 23:00-07:00. In specific the preheating schedule starts at 02:00 and gradually increases the set point until 20°C is reached at 08:00. Precooling schedule on the other hand is initiated at 05:00 and is gradually lowered down to 25°C at 08:00.

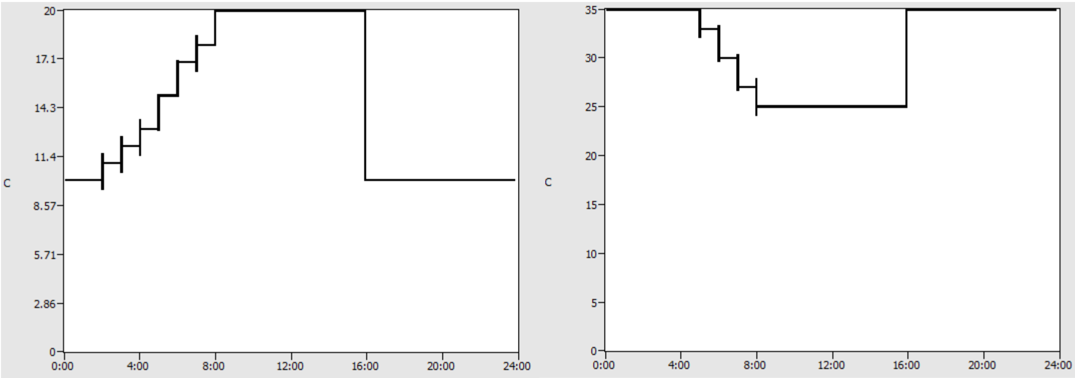

Figure 4:Heating (left) / Cooling (right) schedule for HVAC system in preconditioning scenario.

4 DISCUSSION

Simulation results were analysed and evaluated both by visual inspection of the graphical representation of the indoor temperature in various thermal zones but also with the aid of Matlab for the calculation and comparison of energy costs. In figure 5 the energy consumption for the preconditioning scenario is displayed. Energy A and Energy B refer to energy consumption in tarrifs A and B respectively. The comparison between the baseline and optimal preconditioning scenarioassociated energy costs for the duration of one full year is presented in fig. 6.

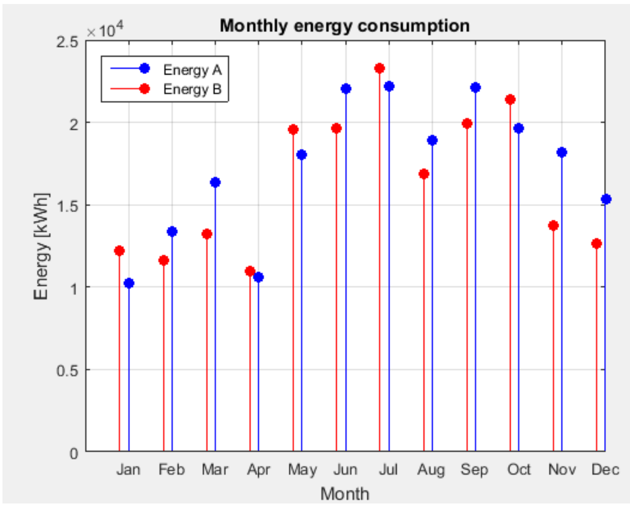

Figure 5: Monthly energy consumption (Energy A, Energy B) during tariffs A and B

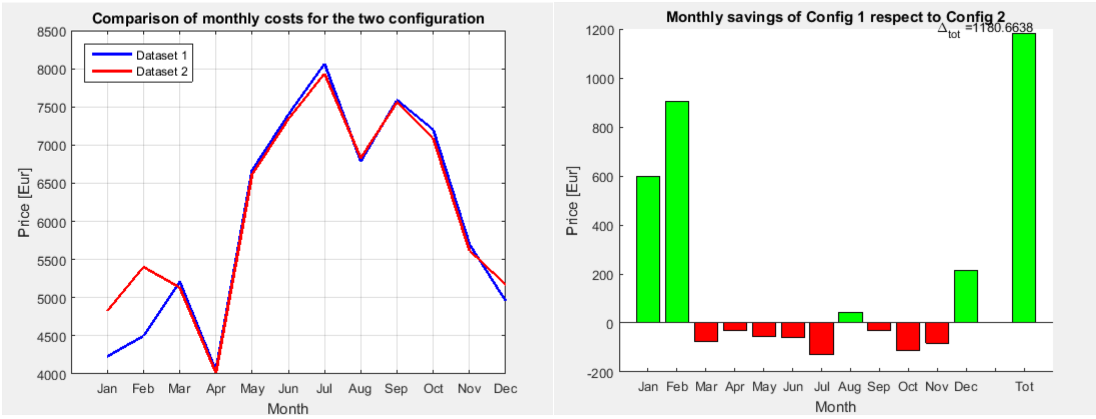

Figure 6: Total energy costs for the baseline and preconditioning scenarios

In fig. 6 it is observed that in January and February the selected schedule (Dataset 1) for preheating performs significantly better compared to the baseline scenario (Dataset 2). In contrast during months March to July and September to November preconditioning leads to increased energy costs. Overall results indicate savings of the order of 2% are achieved along with improved indoor comfort.

5 CONCLUSION

This initial Demand Response approach indicates that in the existing energy tariff scheme there is a relatively small but still significant potential for energy cost reduction by implementing preheating and precooling strategies. Further analysis will be needed to evaluate the actual potential savings of such an approach by applying more elaborate optimisation techniques focusing on varying daily weather and HVAC load profiles. In particular it is evident that an analysis of energy related costs on a daily basis may reveal the actual potential financial savings by implementing a dynamic DR control approach. Further research in this direction involves the implementation of a DR control approach based on genetic algorithm optimisation and load predictions with the aid of a building neural network model.

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