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Internal Combustion Engine controlled by Artificial Neural Network

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Abstract: The paper presents a control strategy concept of a piston engine fueled by Natural Gas as a DG unit obtained by using an Artificial Neural Network. The control strategy is based on several factors and directs the operation of the unit in the context of changes occurring in the market, while taking into account the operating characteristics of the unit. The control strategy is defined by an objective function: for example, work at maximum profit, maximum service life, etc. The results of simulations of the piston engine as a DG unit at chosen loads are presented. Daily changes in the prices of fuel and electricity are factored into the simulations.

1 Introduction

Rising fuel prices combined with an upward trend in electricity consumption are providing strong incentives for research into systems that boost generation efficiency.

An electricity distribution system based on a network of small, interconnected sources is characterized by both load variability and changing electricity prices. This means that the sources will have to adapt to the load not only for local changes, but also as it relates to the market balance between buyers and sellers of power to the grid and changes in fuels markets.

The DG system has many advantages, including very high certainty of supply,high efficiency power generation (both electricity and cogeneration) and high adaptability to changes in demand (both daily and annual). The DG system can be compared in its essence and mode of operation to the Internet or to mobile networks.

Sources in a distributed system can operate in one of many variants, depending on the individual preferences of the operator. One option is to work for maximum profit - increasing the supply of high-margin power sources, another is to boost the longevity of equipment in order to avoid additional starts and stops, and yet another might be to provide maximum subsistence for a customer's needs (e.g. hospitals).

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Most operators will probably devise a blend of factors depending on their individual circumstances. An interconnected network of small sources, and their cooperation with the electricity network might add one extra layer of complexity: the operator may cede control of the source to a larger operator who, through control of a large number of similar sources, may have a power comparable to that of a classic large power plant. A network of sources and combined operational control would change power relations.

Current trends in energy and fuels on the market lends additional influence to all those issues. There are here the following options: operation of the device at a cost below the purchase price (Bid), operation at a cost between the sale price (Ask) and the Bid price; operation at a cost above the Ask price. Additionally, some operators may cooperate with the distribution network to provide system solutions and situations may arise when the source is disconnected from the network ('island operation').

The selection of individual sources working in a distributed system is a complex issue [El-Ela, Allam, and Shatla (2010)]. Until now, research work on source operation in DG has focused on issues of electrical [Hajizadeh and Golkar (2007)] synchronization with the network, the impact of noise generated, etc. Issues relating to long-term source operation are virtually unrecognized and unexplored. The analysis available applies only to selected elements of the work of DG sources.

In [Wang, Kang, Chang, Cao, and Xu (2004)] sources that can operate as a distributed source were classified: (i) Reciprocating engines; (ii) Gas turbines [Jagaduri and Radman (2007)]; (iii) Stirling engines [Corria, Cobas, and Lora (2006)]; (iv) Combination systems based on gas turbines [Tarroja, Mueller, Maclay, and Brouwer (2008)] and reciprocating engines; (v) Small hydro, wind power; (vi) Photovoltaic systems [Maine and Chapman (2007)]; geothermal power plants [Al-Sulaiman, Dincer, and Hamdullahpur (2010)]; (vii) Fuel cells [Hajimolana, Hussain, Daud, and Shamiri (2011); Kupecki and Badyda (2012)]; and (viii) Systems using: biomass Milewski and Lewandowski (2009); Lanzini, Santarelli, and Orsello (2010); Budzianowski (2011) and waste, tides, currents, waves and warm seas.

Most available studies almost exclusively concern the issues of electrical and electronic collaboration between the DG source and the power system [Wang, Kang, Chang, Cao, and Xu (2004)]. The time periods considered there are below 1 second. The proposed variants are closely related to the network source (e.g. through an intermediate network of DC). Issues are also dealt with the same power grid work [Paatero, Sevon, Lehtolainen, and Lund (2002)] including the determinants of transmission. The behavior of the power grid of connected sources distributed in emergency situations [Rodriguez, Timbus, Teodorescu, Liserre, and Blaabjerg

(2007)] also on electrical issues was also analyzed.

Control of multiple DG sources via the Internet was subject to study [Sonderegger (2001)], which also took into account the economic aspects of making sources work together. A simulator running in real mode was created [Ocnasu, Gombert, Bacha, Roye, Blache, and Mekhtoub (2008)] to analyze power source co-operation with the network, but it only studied electric co-operation with the network source. An analyzed time frame of less than 100 micro seconds was concerned. Analyses of the work of the same sources from the standpoint of efficiency and power were also carried out, as well as opportunities to work in co-generation [Milewski, Miller, and Salacinski (2005)]. There were attempts to use artificial intelligence to predict the safe operation of sources involved in the distributed system [Rezaei and Haghifam (2008)].

Economic issues of implementing a DG system were analyzed, among others in [Ho, Wenger, and Farmer (1996)]. Attention was paid to the environmental aspects of the application of DG sources on a larger scale. Technical and economic analysis and a comparison of a piston engine with a μ-gas turbine is presented in [Arteconi, Brandoni, and Polonara (2009)], which implies that the piston engine achieves a positive NPV after 5 years (for μ-turbine, this time is almost 8 years).

Decentralized systems are beginning to prevail over centralized models. Very eloquent examples, schematically, are provided by mobile phone networks and the Internet. It is expected that Distribution Generation [Ackermann, Andersson, and Soder (2001)]consisting of many small units will dominate in the near future. In this system, electricity will be produced by small sources installed directly alongside consumers of energy and working mainly to meet their needs. These sources must meet specific requirements including: high generating efficiency, providing most of the energy needs of a facility and possibly providing a small amount of delivered fluids (such as fuel only).

The Artificial Neural Network (ANN) can be applied to simulate an object's behavior without an algorithmic solution merely by utilizing available experimental data. Simultaneously, the ANN can make the model more general, which means that model gives accurate results for data other than that used in training processes.

An overly complex network can be trained with extraordinary accuracy, which means that the network becomes noise dependent (overfitting). Overfitting means the network has memorized the training examples, but has not learned to generalize to new situations. To improve network generalization a network can be used that is just large enough to provide an adequate fit. The simplest architecture of the network was found in each case, to avoid overfitting. If a small enough network is used, it has insufficient power to overfit the data. Further, optimal regularization parameters were applied in automated fashion (Bayesian). This approach does not require dividing the database into two parts: training and testing. Bayesian regularization makes a model generalized, which is the main advantage of applying this algorithm to the network teaching process. This means that the model can be validated by the same batches of data. The weights of the network were assumed to be random variables with specified distributions. The regularization parameters are related to the unknown variances associated with these distributions. Estimation of these parameters can be made using statistical techniques. A detailed discussion of the use of Bayesian regularization, in combination with Levenberg-Marquardt training, can be found in [Foresee and Hagan (1997)]. When using Levenberg-Marquardt training with Bayesian regularization, it is important to let the algorithm run until the effective number of parameters has converged.

The "black box" model, based on ANN, generates an answer immediately after input data are obtained. The ANN-based model can predict the object behavior based merely on the available experimental data taken from experimental investigations. The model can generalize the object behavior for both inter- and extrapolations without knowledge of the physical relationships [Chaichana, Patcharavorachot, Chutichai, Saebea, Assabumrungrat, and Arpornwichanop (2012)].

The available data on the use of artificial neural networks to predict the demand for electricity date back to the early 90s. In [Kiartzis, Bakirtzis, and Petridis (1995)] a model (based on artificial neural networks) is used to predict the load profile for the next 24 hours and for the very next hour was presented. The input data for the simulation were: the load profile of the two previous days and the forecasted minimum and maximum ambient temperature. The model was tested for the data of one year from the Greek interconnected power system. The resulting average absolute prediction error for this period was 2.66%. In turn, [Paarmann and Najar (1995)] presented a model which automatically adapts and is used to predict the daily and weekly demand for electricity. The error obtained in this way ranged from 2.5 to 5.1%. Similarly, the authors [Sforna and Proverbio (1995)] used artificial neural networks for online load prediction. This model was tested in Italy on data from 15 February to 31 July 1993, yielding an average error of 1.93% (for maximum load) and 2.65% (for minimum load). [Hobbs, Helman, Jitprapaikulsarn, Konda, and Maratukulam (1998)] presented a fairly comprehensive assessment of the results of the use of artificial neural networks by various centers for short-term electricity load and gas demand forecasting. However, the authors of [Tamimi and Egbert (2000)] presented the benefits of a merger of Fuzzy Logic (FL) with an artificial neural network, compared to the Autoregressive Moving Average (ARMA) model for load forecasting. [Abraham and Nath (2011)] compared the neuro-fuzzy system (a combination of artificial neural network (ANN) with a fuzzy neural network

(EFuNN)) with Box-Jenkins autoregressive integrated moving average (ARIMA), a program to predict the load used by Victorian Power Exchange (VPX) and also compared with an artificial neural network only. All compared options were tested on the data describing the demand for electricity in the state of Victoria, Australia. These comparisons showed the neuro-fuzzy system was the best.

The authors [Hsu and Chen (2003)] took a slightly different subject, focusing on the use of artificial neural networks to predict the peak demand for electricity in Taiwan. The learning networks were made on data from 1981 to 1997, and testing - from 1997 to 2000.

In [Beccali, Cellura, Brano, and Marvuglia (2004)] a model was proposed to predict the load for 24 hours based on weather data (temperature, relative humidity, total solar radiation). The model was trained on historical data for parts of the electricity grid in Palermo (Italy) during the period 2001–2003. The average prediction error for this case was 1.97%. In turn, [Azadeh, Ghaderi, Tarverdian, and Saberi (2007)] shows an integrated genetic algorithm (GA) and artificial neural network used to predict electricity consumption in the Iranian agriculture sector. The genetic algorithm was tested on data from 1981 to 2005, while the artificial neural network was used to predict electricity consumption to 2008. An algorithm was presented in [Azadeh, Ghaderi, and Sohrabkhani (2008)] based on an artificial neural network, and was used to predict monthly electricity consumption in Iran from March 1994 to February 2005.

A hybrid model was presented in [Amjady and Keynia (2009)] to predict hourly electrical load using the wavelet transform (WT), neural network and evolutionary algorithm (EA). The model created in this way was tested on data for New York for 1 July 2004, yielding an average prediction error of 2.06%. In [Kavaklioglu, Ceylan, Ozturk, and Canyurt (2009)] a model was presented that used artificial neural networks to predict electricity consumption in Turkey. The inputs to the model were economic indicators such as gross national product, population and import and export. The second version of the model only had to input the ratio of imports to exports and time. The result of this work was a prediction of electricity consumption in Turkey until the year 2027 using data from 1975 to 2006, along with the previously mentioned economic factors.

In contrast to previous examples in [Adam, Elahee, and Dauhoo (2011)] an artificial neural network was used to predict the input data (gross domestic product - GDP, temperature, hours of sunshine and humidity) to a model which forecasts peak electrical load in Mauritius using NHGDP method (non-homogeneous Gompertz diffusion process).

In [Cai, Wang, Tang, and Yang (2011)] a neural network was presented that was based on adaptive resonance theory called a distributed ART and HS-ARTMAP (Hyper-spherical ARTMAP) network to predict electricity load.

As we can see from literature data, the problem with load or demand for electricity forecasting has been pretty well researched, but the ways of using such information for devices working in a distributed generation system have not been analyzed.

2 Theory

2.1 Piston engine

Stationary piston engine LHM80 made by the Chinese company LVHUAN was an analyzed source.

Specification of that unit was shown in Table 1.

Table 1: Specification of LVHUAN LHM80 engine

Parameter	Value (prime/standby)
Rated power, *kW*	64/80
Rated speed, *RPM*	1500/1800
Heat consumption, MJ/kWh	$\leq 9.8(\eta = 0.367)$

The engine efficiency graph (Fig. 1) was based on actual data from the operation of Mephisto engines ([Kwk (2013)]) after they were first normalized and generalized. Changes in the efficiency of the engine during load changes can be approximated by the following relationship:

$$\eta_{rel} = 1,2484 \cdot P_{rel}^3 - 3,0771 \cdot P_{rel}^2 + 2,8448 \cdot P_{rel} \quad (1)$$

where: η_{rel} - relative engine efficiency, P_{rel} - relative power.

Engine efficiency at the actual load is obtained by multiplying nominal electrical efficiency by relative efficiency.

2.2 Artificial Neural Networks

An ANN is a black-box model which produces certain output data as a response to a specific combination of input data. The ANN can be trained to learn the internal relationships and predict system behavior without any physical equations. The ANN consists of neurons gathered into layers. Information is delivered to the neurons by dendrites and the activation function is realized (by the nucleus). Then,

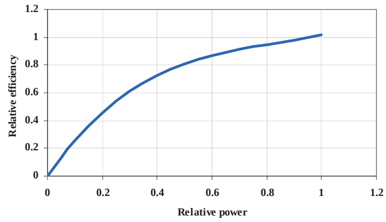

Figure 1: Relative engine efficiency (based on [Kwk (2013)])

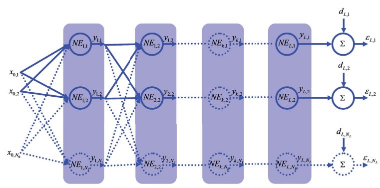

Figure 2: Artificial Neural Network model

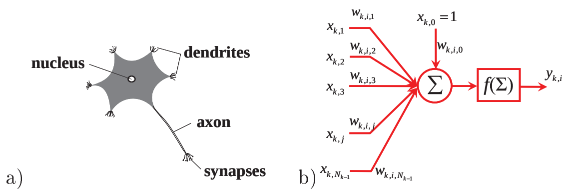

Figure 3: Neuron scheme (a) and its mathematical model (b) [Demuth, Beale, and Hagan (2013)]

modified information is transferred forward by the axon and synapses (see Fig. 2) to other neurons.

Each neuron in the first layer takes the input values, multiplies them by the corresponding weights ($w_{k,i,1}$) and summarizes all these multiplications. Bias ($x_{k,0}$) is added to the sum ($s_{k,i}$). The sum ($s_{k,i}$) is recalculated by the neuron activation function (see Eq. 3) which gives the neuron answer: $y_{k,i}$.

$$s_{k,i} = \sum_{j=0}^{N_{k-1}} w_{k,i,j} \cdot x_{k,j} \tag{2}$$

$$y_{k,j} = f(s_{k,j}) \tag{3}$$

In this study, a hyperbolic tangent sigmoid transfer function was used as the neuron activation function in the first layer, whereas a linear transfer function was used in the output layer (see Fig. 3).

During the model calculations, information proceeds step by step from the first layer to the last one. The answers of the neurons in the last layer are the output parameters of the ANN model (see Fig. 2).

Backpropagation was chosen as the learning process of the ANN. Backpropagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. A detailed description of backpropagation can be found in [Demuth, Beale, and Hagan (2013)]. The governing equations of the process are presented below.

$$s_{k,i} = \sum_{j=0}^{N_{k-1}} w_{k,i,j} \cdot x_{k,j} \tag{4}$$

$$y_{k,i} = f(s_{k,i}) \tag{5}$$

$$\varepsilon_{L,i} = d_{L,i} - y_{L,i} \tag{6}$$

$$\delta_{k,i} = \varepsilon_{k,i} \cdot \frac{\partial f(s_{k,i})}{\partial (s_{k,i})} \tag{7}$$

$$\varepsilon_{k,i} = \sum_{m=1}^{N_{k+1}} \delta_{k+1,m} \cdot w_{k+1,m,i}, \quad k = 1,2,\ldots,L-1 \tag{8}$$

$$w_{k,i,j}^{n+1} = w_{k,i,j}^{n} + 2 \cdot \eta \cdot \delta_{k,i} \cdot x_{k,j} + \alpha \left(w_{k,i,j}^{n} - w_{k,i,j}^{n-1} \right) \tag{9}$$

where: η - learning rate; α - momentum parameter; for a description of the other parameters see Fig. 3 and Fig. 2.

Commercially available software [Demuth, Beale, and Hagan (2013)] was used for the ANN calculations. The Levenberg-Marquardt algorithm was used to accelerate the training procedure. An overly complex network can be trained with extraordinary accuracy, which means that the network becomes noise dependent (overfitting). Overfitting means the network has memorized the training examples, but has not learned to generalize to new situations. To improve network generalization a network can be used that is just large enough to provide an adequate fit. The simplest architecture of the network was found in each case to avoid overfitting. If a small enough network is used, it has insufficient power to overfit the data. Further, optimal regularization parameters were applied in automated fashion (Bayesian). This approach does not require dividing the database into two parts: training and testing. Bayesian regularization makes a model generalized, which is the main advantage of applying this algorithm to the network teaching process. This means that the model can be validated by the same batches of data. The weights of the network were assumed to be random variables with specified distributions. The regularization parameters are related to the unknown variances associated with these distributions. Estimation of these parameters can be made using statistical techniques. A detailed discussion of the use of Bayesian regularization, in combination with Levenberg-Marquardt training, can be found in [Foresee and Hagan (1997)]. When using Levenberg-Marquardt training with Bayesian regularization, it is important to let the algorithm run until the effective number of parameters has converged. The training was stopped by the message "Maximum MU reached". This is typical, and is a good indication that the algorithm has truly converged. A detailed explanation of the training algorithm parameters can be found in [Demuth, Beale, and Hagan (2013)].

The network architecture is indicated in the following way: "number of inputs - number of neurons in the first layer - number of neurons in the second layer"; e.g. 9-7-1 means that the two-layer network consists of nine inputs, seven neurons in the first layer and one neuron in the second layer (the number of neurons in the last layer equals the number of outputs).

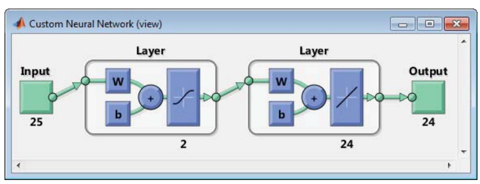

Figure 4: Model of artificial neural network (25-2-24) in MATLAB

2.3 *Construction of chosen variants of ANN*

Based on the performed analysis, it has been found that the most appropriate ANN architecture is as follows: one input layer, one hidden layer and one output layer. The quantity of used neurons in both input and output layers depends on model in/out parameters. The number of neurons in the hidden layer was determined during training procedures.

The network has 25 inputs, of which 24 is the load in each hour of the previous day and one determined day of the week. The output layer consists of 24 neurons, which reflects the forecast demand for every hour during the day and night.

Different types of neuron activation functions were applied for the first and hidden layers (hyperbolic tangent sigmoid) and different for the output layer (linear transfer functions).

The only quantity of neurons in the hidden layer was found by the trial and error method. Networks have been tested from 1 to 25 neurons in the hidden layer. The best configuration turned out to be 25-14-24 because it gave reasonable results with the least number of neurons.

2.4 Costs

In order to reduce electricity costs the possibility of using a dual-zone tariff of electricity in cooperation with a natural gas-powered piston engine was studied in order to benefit from cheaper electricity in the valleys and to produce it oneself in the peaks or to buy it from the mains, depending on what is more profitable.

Fixed costs include license fees for electricity, which for the tariffs used in this analysis are about \$5.2/month gross (tariff G12r relating to power companies: "ENERGA-OBRÓT S.A." and "Energa Operator S.A"). They also include a fixed charge of \$37.71/month gross for gas (transmission & distribution charged by the company "PGNiG").

Variable costs include primarily the purchase of electricity (Table 2) and the scales of the gas group of "PGNiG" in tariff w-2 for fuel only (\$0.415/Nm^3) and tariff E-1A for transmission (\$0.011/Nm^3).

Table 2: Variable costs of electricity by tariff G12r relating to power companies: "ENERGA-OBRÓT S.A." and "Energa Operator S.A"

hours	$/MWh$
7:00-13:00 & 16:00-22:00	0.228
13:00-16:00 & 22:00-7:00	0.091

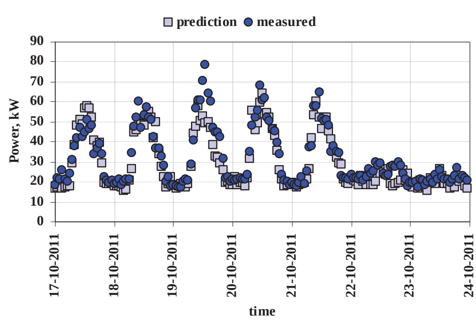

Figure 5: Load prediction vs measured value

Revenues include above all the avoided costs of purchasing electricity at a time when producing it is a cheaper way of meeting demand.

3 Optimal control strategy of a NG piston engine

The neural network created as described above was trained using load data from 08.10.2011 to 15.10.2011 for part of the Institute of Heat Engineering and Central Canteens of Warsaw University of Technology.

After putting on the input of the network information about the load of 16.10.2011 together with information what day of the week it concerns was received a load of 17.10.2011, which was put on the network input together with the information about the day of the week.

This operation was repeated many times to obtain load for the entire week from 17.10.2011 to 23.10.2011.

Figure 5 shows a comparison of results obtained as described above against the real load of the same period.

In the next step, a simulation of engine operation on the load generated by the neural network was performed.

Figure 6 shows the optimal way of meeting demand of part of the complex of buildings using the piston engine and power grid.

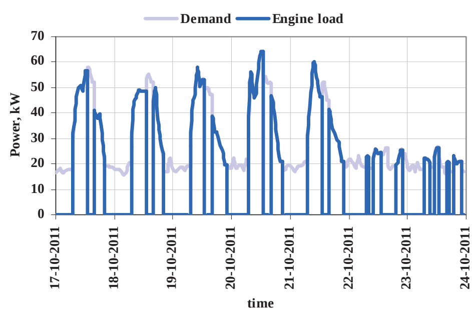

Figure 6: Demand vs optimal engine load

Figure 7 shows the cost of producing electricity and its cost at the optimal operating strategy.

As is shown in Figure 5 the load predicted for the week ahead is fairly close to the measured load. This gives an opportunity for better analysis of the profitability of potential investments.

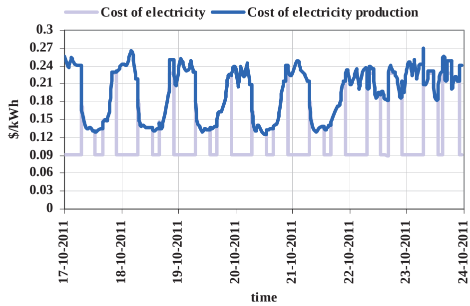

Figure 7: Cost of electricity vs cost of electricity production

The simulation engine work (Fig. 6) done on the load generated by the neural network shows that the engine operates only in the peaks of demand. In the valleys electricity from the grid is so cheap that it is not profitable to operate the engine in this situation.

On Monday (10.17.2011), Tuesday (18.10.2011) and Thursday (20.10.2011), the engine shuts down before the end of the evening peak, which is due to low load and thus the low efficiency of electricity generation. A similar situation occurred on Saturday and Sunday (22.10.2011 and 23.10.2011), when the engine did not run continuously during the peaks and sometimes electricity was purchased from the grid.

The cost of electricity production (Fig. 7) for the previously predicted load ranged from \$0.13/kWh (in peaks) to \$0.27/kWh (in valleys). The cost of electricity at the optimum operating strategy (Fig. 7) during both the peaks and the valleys could not be higher than the cost specified in the tariff G12r of the companies "ENERGA-OBRÓT S.A." and "Energa Operator S.A".

In order to compare the cost-effectiveness of the proposed solution it should be compared with the single-zone electricity tariff by subtracting from each the sum of both the variable and fixed costs for the considered time period. As a reference point the G11 tariff was assumed, relating to the power companies "ENERGA-OBRÓT S.A." and "Energa Operator S.A" (fixed cost - \$3.49/month gross and variable cost - \$0.19/kWh gross).

For the considered week the difference in variable costs was \$287/week. After taking into account the fixed costs, the income associated with the proposed solution was \$278/week.

4 Conclusions

The neural network used to predict the load was proposed and the control strategy for the NG piston engine as a DG source of power is presented. From the investigations performed, it was determined that the most appropriate objective function of the strategy is to operate the engine for maximum profit (defined as avoided costs of buying electricity from the grid). On average, the NG piston engine is started up two times a day: during both the morning and evening peak loads.

Profits from operation of the NG piston engine depend strictly on the load profile and for the case at hand it was $278/week.

Currently, many buildings (e.g. office buildings) have piston engines as emergency power units, but mainly fueled by liquid fuels (gasoline, oil) - which are more expensive than NG. Those units are not used for power generation. If as expected there is further inflation in electricity prices, power units might be considered for power generation exclusively during peak loads. In those cases, investment (installation) costs are incurred, but in the case of large buildings (with a range of MW), the profits could be quite substantial.

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