

## DEAM: A Scalable Dynamic Energy Agents Model for Demand and Supply

Catalina Spataru  
Energy Institute  
University College London  
London, UK  
c.spataru@ucl.ac.uk

Mark Barrett  
Energy Institute  
University College London  
London, UK  
mark.barrett@ucl.ac.uk

**Abstract**—This paper describes an energy system model to investigate the energy demands and supplies of agents connected to an electricity network so as to calculate the possible future half hourly loads imposed on the network. The model predicts the change in scale and shape of current demand profile and forecasts potential changes until 2050, given a mixture of efficiency and supply technologies that might be installed over the coming decades. The model can simulate individual agents at a local distribution network operator level or aggregates of agents at regional or national level. The model accounts for social activity patterns and weather dependent processes including building heating and renewables, thereby simulating variations in demands, supplies and net network load over seasons, days and years. This simulation thereby informs the electricity industry about investments and operations planning. Although the first focus is electricity, the model calculates heat and gas demand and can simulate district heat load.

**Keywords**—demand, DNO, dynamic energy modelling, substation, supply

### I. INTRODUCTION

The traditional electricity network in Great Britain since the 1930s has been driven by a one-way flow from large generation plant through transmission and distribution networks to consumers, with a centralized control of network operations. Under these conditions, network planners have accurately predicted the behavior, the control and the investment needed for their networks. However, new demands and generation sources are added to the system. This will cause significant changes in power flows and alternations on the optimal configuration, operation and control of the power system. It is important to understand the demand at the network level by time of day and season in order to identify in the network possible changes may occur and impact in the future to avoid situations when currents are too high causing over-heating, which in turn may cause outages or significant impact on equipment failure which could draw to high costs. In order to be able to understand such situations, we developed a dynamic energy model, which creates estimates of half-hourly demand and renewable profiles for a given network – local, regional or national. It estimates consumption profiles for customers from configurable models of the drivers of consumption including building and appliance efficiency, heating technology, electric vehicles and socio-economic factors.

This model facilitates the creation of energy demand scenarios for comparison to other analysis. The estimated may be used to further refine the view of measured versus derived data. Moreover, it can determine new customer profiles that can be used to simplify the process of demand estimation and potentially improve the accuracy of the settlement process. The load-profiling concept is not a new one, with data has been collected and analyzed since 1950s such as by the Electricity Council Load Research Programme [6]. Since 1988 when the Electricity privatization opened up the electricity supply market to competition, the use of load profiles for electricity has become more important for company planning. In 1994 part of the programme established by the Profiling Taskforce, eight basic types of profile classes, which represent different categories of customer that have different patterns of load during the day, were defined to better model the different metering configurations in the electricity supply market [6]. These profiles are: Domestic Unrestricted Customers, Domestic Economy 7 Customers, Non-domestic unrestricted customers, non-domestic economy 7 customers, non-domestic maximum demand customers with a peak load factor of less than 20%, non-domestic maximum demand customers with a peak load factor between 20% and 30%, non-domestic maximum demand customers with a peak load factor between 30% and 40%, non-domestic maximum demand customers with a peak load factor over 40%.

### II. MODEL DESCRIPTION

The model is called Dynamic Energy Agents Model (DEAM). The designation “Dynamic Energy Agents Model” is used here to reflect the fact that energy demands and supplies are modelled at the individual agent level (households, businesses, generators, etc.) connected to a node in a network, for example an electricity substation. The model calculates the energy flows for these agents (either domestic or non-domestic consumers, or energy suppliers), to identify the possible future loads imposed on the network. Consumers engender demands for different end uses (lighting, heating, etc.) and meet these end uses using energy converters (boilers, solar panels, etc).

Load curves for consumers depend on their annual energy consumption for different end uses, activity profiles across the day, week and year, and on the response of people and technologies such as buildings and heat pumps to weather.

The load is calculated for each end use in order to allow the effects of social activity patterns, weather, and of changes such as insulation, heat pumps or more efficient lighting. It is particularly important to estimate loads under peak conditions – e.g. extreme winter conditions – as these strongly determine the installed capacity of energy supply system components. Fig. 1 shows the basic structure of the model.

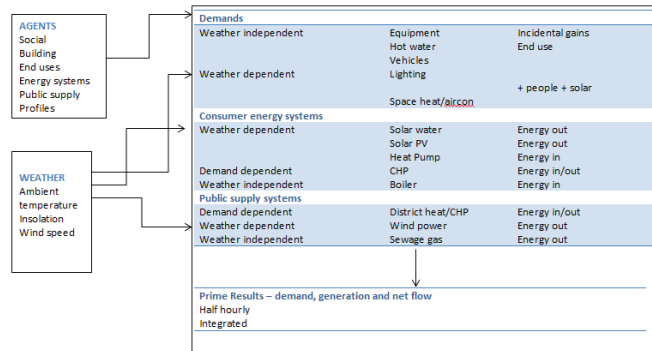


Figure 1. Model diagram.

#### A. Domestic and Non-Domestic Sectors

In order to estimate and project total demands on a particular network it is necessary to consider all connected loads and generators in the domestic and non-domestic sectors (NDS).

##### 1) Domestic sector

The energy used by households first depends on social factors, particularly household size, occupancy, internal temperature, and appliance use. The demand for space heat depends on physical factors: the form of the dwelling (detached semi-detached, terraced, mid-terraced, flat), its dwelling size and envelope efficiency as determined by insulation, roofing material, window area and so on; size, number of occupants, heating control system facilities, orientation of the house (solar gain); climate. There are a wide variety of parameters affecting energy use of individual dwellings, for example, dwelling type (this affects external heat loss area) and size; heating system and fuel; weather, varying both with location and by year. Various databases were considered and the information collated into a single agents database (Agentsdb). The primary data source used is the English Housing Survey (EHS) data; with the use of other data sources to provide the necessary information. The EHS is an annual survey of dwelling stock profile by age, type, size and location of dwellings in England, carried out on behalf of the Department of Communities and Local Government [4]. The results are based on a sample of 16,217 dwellings and 15,604 households. The survey provides outputs such as: type of dwellings; the energy performance of dwellings; the uptake of heating and insulation measures in the housing stock and its current performance in terms of energy

efficiency and the carbon emissions associated with heating, lighting and ventilating the home.

##### 2) Non-domestic sector

Non-domestic buildings account for about 20% of UK energy consumption according to UK department of Communities and Local Government [4]. This proportion increases in dense urban areas where non-domestic buildings are generally concentrated. The non-domestic building stock has a floor area of about 1.74 Mm<sup>2</sup> around 35% of the building area in England [4]. The diversity of buildings types within the non-domestic UK building stock and the scarcity of reliable data have been identified as difficulties in the attempts to model non-domestic energy consumption. Non-domestic energy use primarily occurs in buildings driven by the same types of social and physical factors, which means the same model may be used for domestic and non-domestic agents. The national database of non-domestic sectors includes an estimated breakdown of energy consumption by end use.

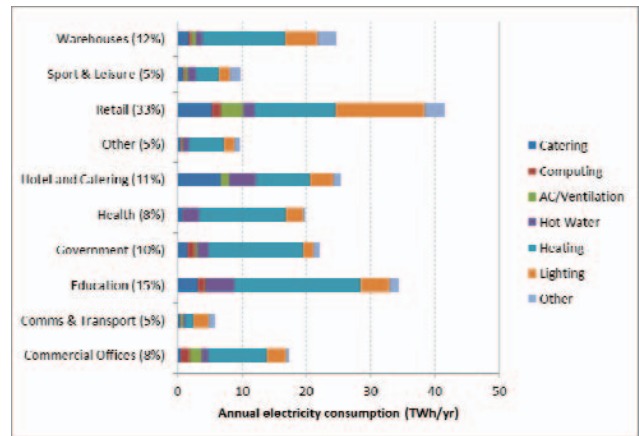


Figure 2. Service subsectors annual electricity consumption in the UK by end use (Data Source: [2]).

The main non-domestic sector agents comprise:

*Services agents* - this includes shops, offices, warehouses, health, education, leisure, hotels. A substantial fraction of the energy used in these sectors is used in building and other services (heating, lighting etc.) as shown in Fig. 2: the largest sub-sector consumer of electricity is retail, and that lighting and heating are large components.

*Industry agents* - the principal subsectors are iron & steel, non-ferrous metals, mineral products, chemicals, mechanical engineering & metal products, electrical & instrument engineering, vehicles, food, drink & tobacco, textiles, leather, clothing, paper, printing, publishing, construction, other.

Fig. 3 shows a breakdown of industrial energy use. Making accurate estimates of efficiency savings and the effects of new technologies in industry is more problematic because of the heterogeneity of industrial processes.

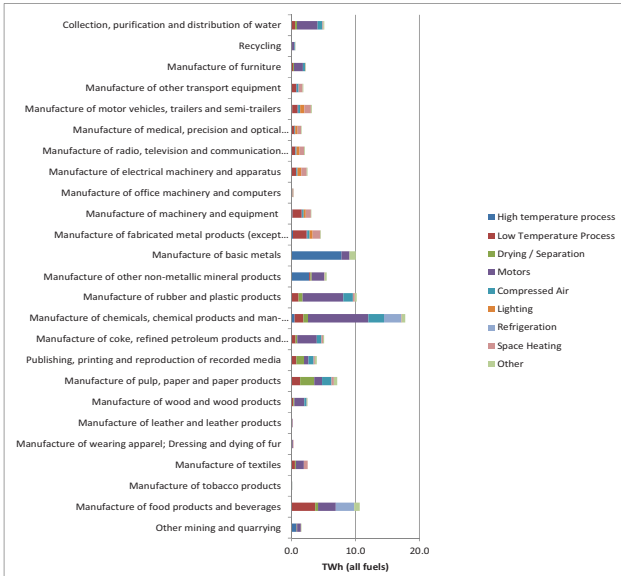


Figure 3. Industry subsectors energy by end use (Data Source: [2]).

information about the basis for energy demands for heat, electricity and gas. Therefore a complex process coupling given primary data there are, coupled with default assumptions has been used. As an example, Fig. 4 shows some of the databases and relations used for modelling a substation. The industry provided connectivity database is used as the master list of connected agents, and other data sources are matched to this using various techniques such as postcode and agent name searching, and estimation for missing or, invalid data. Some of the databases for non-domestic sector are: the Display Energy Certificate Database [5] – a database which contains information on the type of public building, annual electricity demand. The UK marketing database (UKMD) [7] including 2.2million enterprises which describes the nature of the business activities (which defines the type of building and energy demand profiles used by the model) and the number of employees in the business (which informs estimates of the size of building. Derived attributes, such as the specific heat loss factor, are calculated with default assumptions. Fig.5 shows the logical data-modeling diagram.

### B. Database preparation process

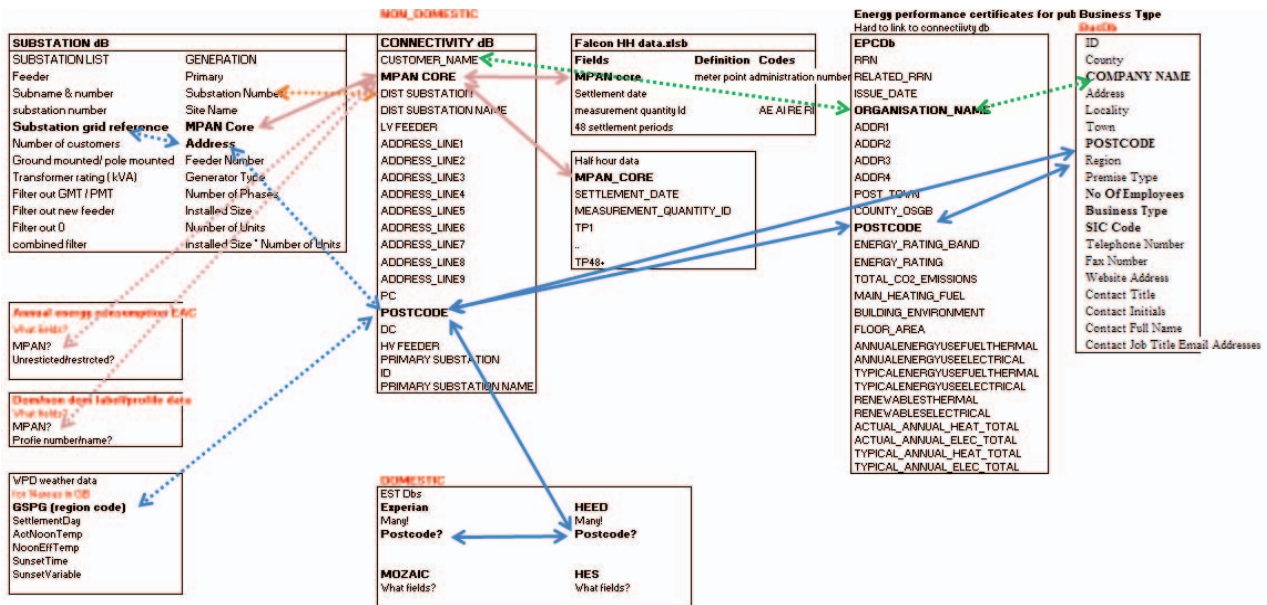


Figure 4. Logic diagram for linking databases.

For non-domestic agents there are no available comprehensive databases with all the data required. This lack of data is partly due to heterogeneity (which means high costs to collect data), partly because of commercial sensitivities and partly because these sectors have lower political priority and use less energy than the domestic sector. Due to the diversity and complexity, various data were combined with data processing to estimate building characteristics and energy demands and will form the base from which a richer database will be generated providing

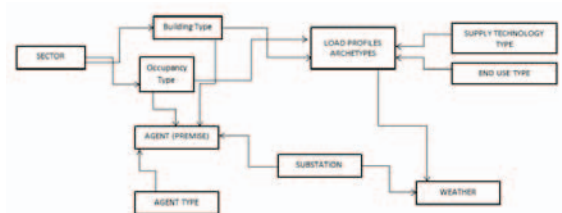


Figure 5. Logical data modelling diagram.

The steps used in the process are:

- S1: Define all required inputs and the structure of model inputs
- S2: Obtain and analyse extracts from all primary data sources
- S3: Prepare source to target mapping, highlighting any gaps and issues
- S4: Create and maintain data dictionary
- S5: Develop estimating rules and assumptions to plug any gaps

Various assumptions were made and rules have been applied. It has been assumed that floor area is the product of plan area and number of floors. Other key attributes considered are: ambient temperature, comfort temperature, (heater) efficiency, metering type, number of electric vehicles, public generation profile ( $P_{gen}$ ), monthly demand profile ( $P_m$ ), normalisation profile ( $P_{norm}$ ), weekly demand profile ( $P_w$ ), solar PV potential, space heat loss (factor), sunlight, wind speed.

### C. Drivers

#### 1) Weather

The weather variables are ambient temperature ( $T_{amb\_hh}$  (°C)), solar energy ( $Solar\_hh$  ( $W/m^2$ )), and wind speed (wind speed (m/s)). Weather data are either from a local weather station or, if not available, modelled using functions with a random factor for monthly and diurnal variation based on historical data. Extremes such as very cold, dark winter days when peaks may occur can be modelled.

Fig. 6 shows illustrative winter's day synthetic meteorology for ambient temperature, wind and solar.

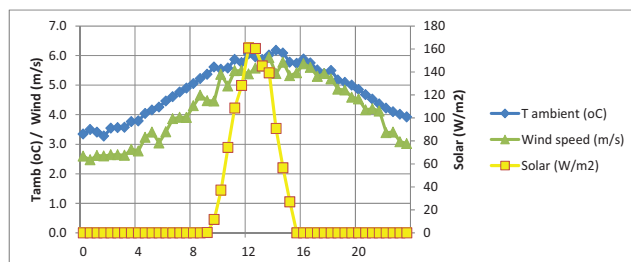


Figure 6. Weather profiles.

#### 2) Profiles and occupancy periods

There are two types of profiles in DEAM: occupancy periods and profiles relating to human activities over the half hours (hh), weekdays (w) and months (m). Occupancy periods define when buildings are occupied by active people and the building environment related services of space heating, air conditioning and lighting are assumed to be provided. These are defined by time clock settings for two on/off periods. A period profile is where a number is given for each time interval (hh, w, m) within that time interval that gives the percentage index over the period of a consuming activity. Each agent has its own general 'activity' triplet of  $P_m$ ,  $P_w$ ,  $P_{hh}$  describing their daily,

weekly and monthly patterns of use of buildings and other services such as refrigeration or hot water.

### D. Energy Demand Calculations

Two basic types of demand are modelled – weather independent and weather dependent. The individual profiles for each load type can be aggregated to generate the total networkload profile. These profiles can be generated on an annual basis for different representative days: winter peak, winter average and summer average, summer peak.

#### 1) Weather independent demands

These demands are assumed to depend only on social activity profiles with the influence of weather being negligible. Given an annual demand of  $E(kWh)$  for an end use, we may calculate the average power  $Pow_{AnnAv}(kW)$ . Then given monthly use patterns  $P(m)$ , weekday  $P(w)$  and half hourly  $P(hh)$ , we can calculate the power demand in any half hour:

$$P_{hh}(kW) = Pow_{AnnAv} \times P(m) \times P(w) \times P(hh) \times F_n \quad (1)$$

where  $P$  are normalised to annual totals using the factor,  $F_n$ .

In order to calculate the half hourly demand profiles for the 19 different LV feeder types within the DEAM model, it was necessary to develop a set of individual point loads for different building types. This led to profiles being generated for a number of domestic and non-domestic agents types. The profiles varies significantly between building types, depending on factors such as size, age, building use, construction type, occupancy. Fig. 7 provides profiles for a weekday for different end use: computing (ITC) and hot water (HwA).

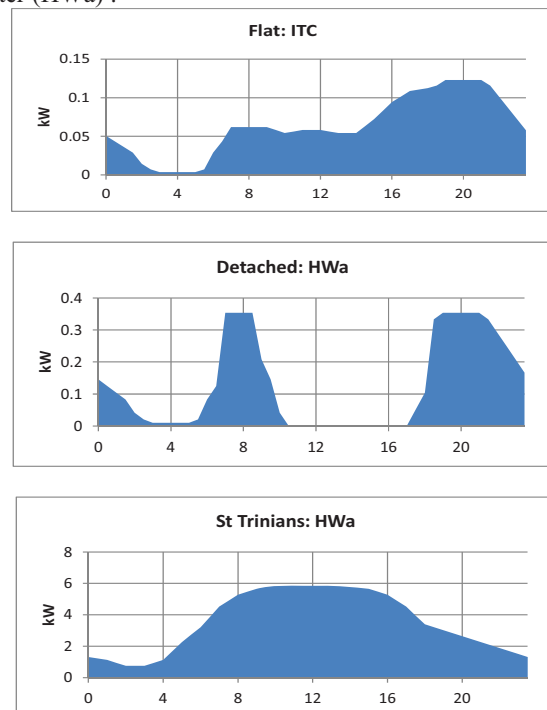


Figure 7. Example of demand profiles for a day.

These illustrate diversity in terms of peak demand.

## 2) Weather dependent demands

Space heating, air conditioning and lighting vary diurnally with meteorology. Other demands such as water heating, refrigeration also vary seasonally because of ambient temperature.

### a) Lighting demand

The demand profile for lighting is given by:

$$\text{Lighting Demand} = \text{Darkness} \times \text{Annual AvgPower} \times \text{PrPeopSpac} \quad (2)$$

$$\text{Darkness} = (1 - \text{Solarhh}/1000)^4 \quad (3)$$

### b) Space heat

For space heating, DEAM has two modes of calculation – a steady state mode and a dynamic mode accounting for thermal capacity. For steady state, the profile that applies to space heating ( $\text{PrPeopSpac\_hh}$ ), is a measure of how much a building is heated or lit and can be written as

$$\text{PrPeopSpac\_hh} = P_m \times P_w \times P_{hh} \quad (4)$$

Space heat demand is driven by the difference between internal and external temperature and the specific loss factor (SLF) of the building ( $W/^\circ K$ ) minus the incidental heat gains  $\text{IncGains}$  ( $W$ ) from people, appliances, passive solar heating, etc.

The steady state space heat load ( $W$ ) defined as

$$\text{SpaceHeat} = [(T_{\text{comf}} - T_{\text{amb}}) \times W - \text{IncGains}] \times \text{PrPeopSpac} \quad (5)$$

where  $W$  is the specific heat loss ( $W/^\circ C$ )

Examples of space heat profiles are given in Fig. 8. The delivered energy for heating is calculated thus:

$$\text{Delivered Energy} = (\text{SpaceHeat} + \text{Hotwater}) / \text{Heater Efficiency} \quad (6)$$

The variation of heat pump efficiency is calculated.

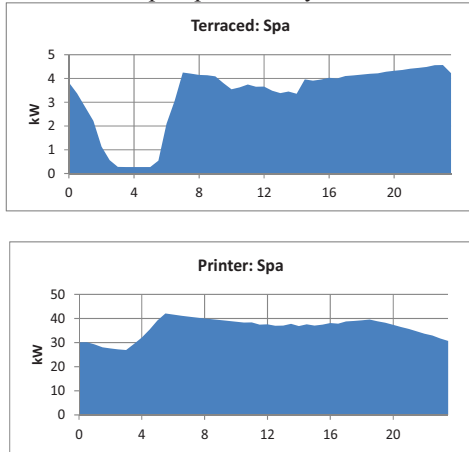


Figure 8. Weather dependent demands profiles.

## E. Consumers generation

These systems convert energy or generate on the consumer side of the meter. To determine the delivered electricity requirement it is necessary to account for the performance of end user energy systems. For example, the solar PV generation (SPV) for an agent ( $W$ ) is calculated as:

$$\text{SPV} = PV\text{area}(m^2) \times \text{Solar\_hh}(W/m^2) \times PVEfficiency \quad (7)$$

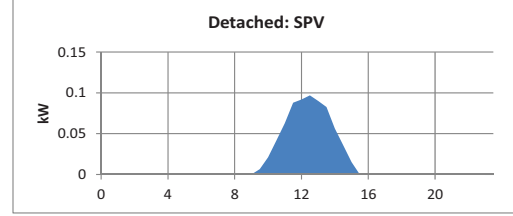


Figure 9. Example of solar PV profile for detached house.

## F. Public supply

DEAM also calculates or uses exogenous data for public generation input to the network between the consumer and network in order to calculate the total net load on the network. The main reason for this is to evaluate the accuracy of the model by comparing model results with flows measured at the network transformer which include private and public generation.

Wind turbine generation  $WTu$  ( $W$ ) is calculated by the following expression:

$$WTu = kw \times (\text{Wind}(m/s))^3 \quad (8)$$

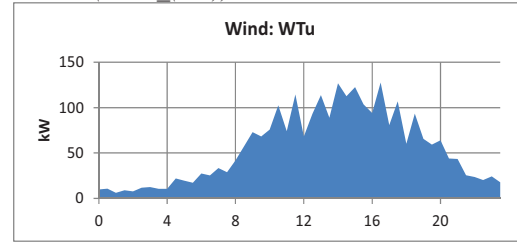


Figure 10. Wind profile.

CHP generation  $CHPGen$  ( $W$ ) is calculated as a constant fraction of the aggregate district heat load  $DHTot$  ( $W$ ) thus:

$$CHPGen = k_{CHP} \times DHTot \quad (9)$$

Figure 11 shows CHP generation arising from three connected loads.

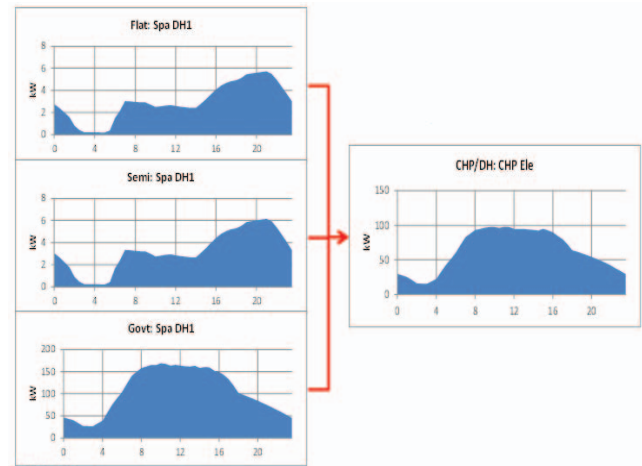


Figure 11. Seasonal demand profiles.

### III. RESULTS – PROFILES

The demands and private and public supplies may summed for each half hour across the sample days of the week and the months to give total demands and supplies and thence find the net total network loads under different social activity and meteorological conditions. The aggregate half-hourly modelled demand by for sub-sectors is illustrated in Fig. 12 and aggregate estimated supply in Fig. 13.

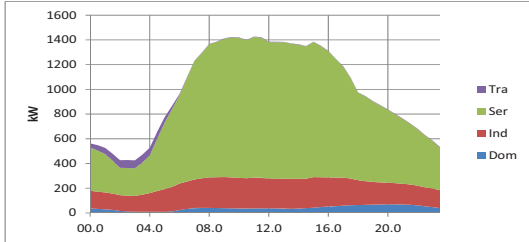


Figure 12. Aggregate demand.

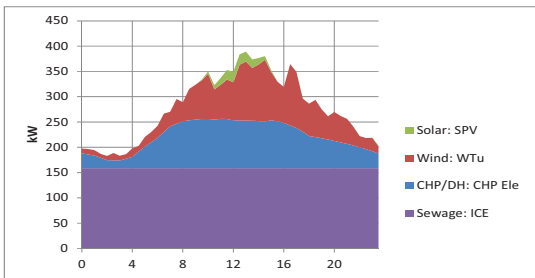


Figure 13. Aggregate supply.

The net load is the difference between the total demand and total generation, as illustrated in in Fig. 14.

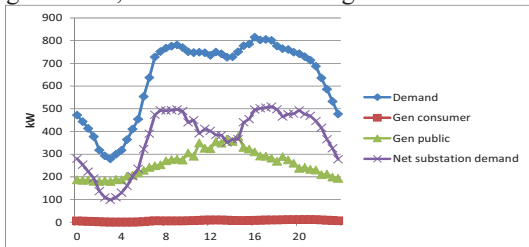


Figure 14. Net load on substation.

### IV. ONGOING EVALUATION

DEAM results have been compared with measured transformer flows during the studies with the electricity industry. The degree of difference is variable and it is hard to ascertain whether data input or model errors cause differences. However, the analysis of differences has so far

led to the conclusions that the model is accurate enough to improve the industry's understanding of factors affecting network flows.

### V. CONCLUSIONS

In this study we have described the need for, and a short description of DEAM model, which is used to aid electricity industry planning in a future where most agree there will be electrification. Using the data structure and algorithms in the model, it is possible to explore how certain energy policies might affect electricity systems in the future. These policies might aim at high levels of implementation of electric heating, electric vehicles and solar PV. Such implementation will generally increase electrical energy demand and peak flows, and the space heating will increase weather dependency and unpredictability. Counter to these increases will be reduction in demand that might be made through building and appliance efficiency. At the base of these scenarios are demography and production in non-domestic sectors and variants of these can be modelled. DEAM can also serve as part of the basis for devising 'smart' control strategies for networks.

The model is being elaborated and extended (<http://www.ucl.ac.uk/energy-models/models/deam>). Enhancements include modeling estimated social (e.g. theft) and physical losses (e.g. ohmic heating) on the network. It will also serve as a basis for modelling gas and district heat demand. It will be applied for modeling cities and possibly other electricity networks.

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