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## A multi-energy system optimisation software for advanced process control using hypernetworks and a micro-service architecture

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### Abstract

This paper describes a multi-energy system optimisation software, “Sustainable Energy Management System” (SEMS), developed as part of a Siemens, Greater London Authority and Royal Borough of Greenwich partnership in collaboration with the University of Nottingham, Nottingham Trent University and Imperial College London. The software was developed for application at a social housing estate in Greenwich, London, as part of the Borough’s efforts to retrofit the energy systems and building fabric of its housing stock. Its purpose is to balance energy across vectors and networks through day-ahead forecasting and optimisations that can be interpreted as control outputs for energy plant such as a water source heat pump, district heating pumps and valves, power switchgear, gas boilers, a thermal store, electric vehicle chargers and a photovoltaic array. The optimisation objectives are to minimise greenhouse gas emissions and operational cost.

The tool uses Hypernetwork Theory based orchestration coupled with a microservice architecture. The distributed nature of the design ensures flexibility and scalability. Currently, microservices have been programmed to forecast domestic heating demand, domestic electricity demand, electric vehicle demand, solar photovoltaic generation, ground temperature, and to run a day-ahead energy balance optimisation. This paper presents the results from both domestic heat and electricity demand forecasting, as well as the overall design and integration of the software with a physical system.

The works build on that of O’Dwyer, et al. (2020) who developed a preliminary energy management software and digital twin. Their work acts as a foundation for this real-world commercialisation-ready program that integrates with physical assets. © 2021 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

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*Keywords:* Multi-energy systems; Energy optimisation; Predictive algorithm; Hypernetwork theory; Microservice architecture

### List of abbreviations

BMS	Building Energy Management System
DB	Database
EVs	Electric Vehicles
Hn	Hyper network
HP	Heat pump
HT	Hypernetworks Theory
SEMS	Sustainable Energy Management Systems

## 1. Introduction

The high energy demand density and limited space for renewable generation in an urban setting poses significant challenges to decarbonisation goals. Electrification of heating and transport through increased uptake of heat pumps (HP) and electric vehicles (EV) has the potential to dramatically reduce the environmental impact of the energy landscape [1], however, suitable energy management strategies are required to ensure that coinciding demand peaks across different vectors do not result in excessive strain on grid infrastructure [2]. Furthermore, the demand must be managed to effectively utilise renewable generation sources supplying power to the grid [3] while reducing the cost burden for the end-user. This type of flexible demand management can be achieved by appropriately shifting and storing the demand arising across different energy vectors, but suitable tools are needed to tackle the complexity of such a multi-vector problem. Of particular importance are models and forecasting methods that can be used to predict future system states as well as optimal control approaches that can use these predictions to determine optimal operational solutions to multi-objective control problems.

As urban data infrastructures become more widely established, opportunities emerge to make use of techniques from machine learning and data science for forecasting and decision-making in energy management strategies. In Wang et al. [4] for example, a long short-term memory learning model is applied for district-level building energy modelling, while for more general district level energy forecasting, Ahmad and Chen [5] compare the performance of three machine learning algorithms. Aside from forecasting, optimal control methods have been applied for real-time operational decision-making in the energy domain, showing clear advantages compared to more traditional approaches [6], with a review of different strategies provided in Mohammadi et al. [7]. Achieving the goals of forecasting and optimisation in a transferable and scalable manner remains a challenge however, with components, data architectures and system hierarchies potentially varying greatly in different contexts. Software tools are needed that can successfully deploy optimisation and forecasting methods in a consistent, replicable manner.

This paper introduces the structure and components of a multi-energy system optimisation software developed by a team at Siemens, the University of Nottingham, Imperial College London and Nottingham Trent University, and is an extension of the work by O'Dwyer et al. [8]. The software tackles the challenge of scalability and transferability by using a Hypernetworks Theory (HT) based approach to choreograph the various modular data collection, forecasting and optimisation components, ensuring consistent orchestration. The paper also covers details of the test site where the software is to be applied and a summary of the results from two microservice predictive algorithms.

## 2. Test site

The control methodology was developed for testing at the Ernest Dence estate, Greenwich, London — a demonstrator for the H2020 Sharing Cities project [9]. The estate is made up of 95 one to four-bedroom social housing apartments over 3 buildings — Aylmer House, Gifford House and Jennings House. The estate has a total floor area of 7320 m<sup>2</sup>.

## 2.1. Energy system

Pre-retrofit, the space heating and domestic hot water was provided by three centralised gas boilers. Space heating was supplied directly from the heat network using control valves to regulate flow through radiators. Domestic hot water was supplied from individual hot water tanks within each dwelling.

Post-retrofit an energy centre containing a groundwater source HP and back-up gas boilers connected to a 10 m<sup>3</sup> thermal store is used. Additionally, building fabric energy efficiency measures such as loft insulation were installed enabling comfortable low-temperature heating. Apartment heat interface units replaced water tanks and control valves to provide direct connection space heating and instantaneous hot water via flat plate heat exchangers. High-temperature radiators were removed and replaced with those suitable for flow and return temperature of 60/30 °C. Heat distribution pipes have been rerouted to minimise the thermal length and insulated to prevent heat losses.

In future there may be a 100 kWp solar photovoltaic (PV) array and ten 7 kW onsite EV chargers installed. They are also considered in the software optimisation.

## 2.2. Heat and electricity demand

Fig. 1 illustrated whole building heat demand data over 3 years, including SH and DHW. Data were simulated with EnergyPlus [10] and Ptolemy II [11] digital twin software and was used to develop heat demand forecasting algorithms that inform the energy system optimisation.

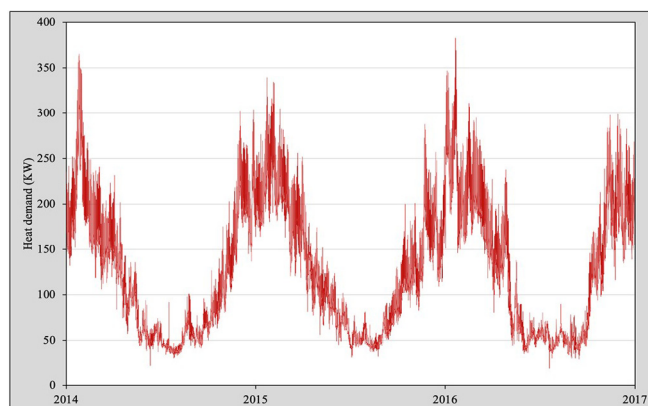


Fig. 1. Heat demand profile Ernest Dence Simulated with EnergyPlus.

Fig. 2 represents a typical week's building electrical load data for the Ernest Dence Estate. Four years of data were simulated using an adapted version of the CREST demand model [12]. Again, energy demand data was used to develop forecasting algorithms to inform the system energy optimisation.

## 3. System architecture

All of the energy assets have direct low-level control internally (see Layer 1, Fig. 3) — for example, the gas boilers will regulate their own firing and pumps. Medium-level control, with a system view, will be done by a building management system (BMS) (see Layer 2, Fig. 3). Whereas high-level control, taking into consideration the whole system and external factors such as variable prices, carbon factors and demand forecasts will be done by a cloud hosted SEMS (see Layer 3, Fig. 3). The SEMS performs an energy optimisation and suggests how to best operate energy assets. By leaving direct control to local controllers all safety-critical scenarios are covered.

### 3.1. Hypernetwork theory

The software uses a Hypernetworks Theory (HT) based orchestration coupled with a microservice architecture. Hypernetworks (Hn) were first introduced in [13], and developed in Johnson [14,15,16] and Johnson et al. [17]. HT

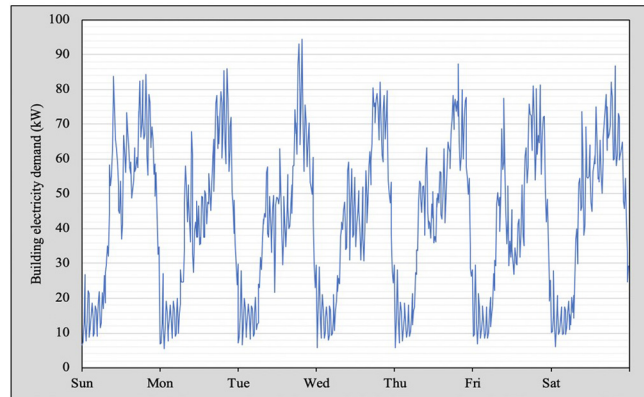


Fig. 2. Weekly domestic electricity demand Ernest Dence in mid-January. Simulated with a modified CREST demand model.

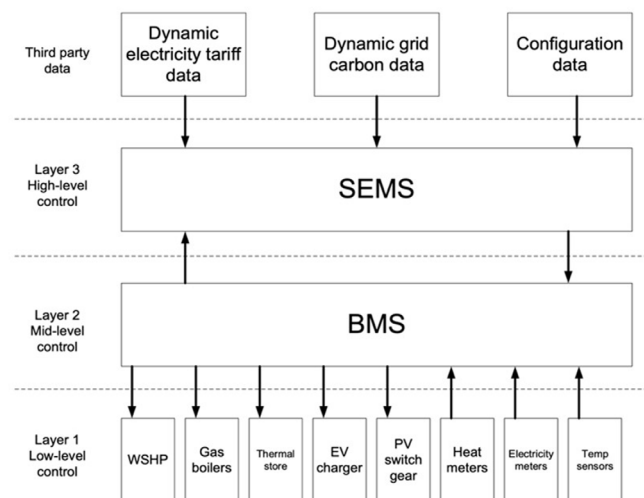


Fig. 3. Control layering at the Ernest Dence Estate, Greenwich, London.

was chosen over other methods as it allows for the explicit definition of a model to clearly collect and process data from numerous sources whilst applying different algorithms at each state. The model can be executed concurrently and allows for different results to be generated for different overlapping models, for example, both real-time execution and forecasting from the same set of inputs and calculations.

In simplistic terms the Hn is a multilevel, multidimensional structure used to describe systems. The primary concepts underpinning HT are quite simple. The Hn has a backcloth [18,19] structure. The structure can be a representation of the physical, some logical or mathematical structure, or even a combination of both. An important feature of the Hn is that it can represent an overlap of systems, or views of systems, that enable models to be created that provide individual and combined results.

The Hn itself consists of interrelated Hypersimplices which form levels by grouping nodes or vertices. Each vertex is a part, and by grouping the parts in logical ways they form a whole, and each whole can then be a part of some other whole, and so it goes on forming levels. The collection of parts is known as a simplex. Each part can form more than one whole and, in this way, provide the overlap amongst systems. The logical way in which we group these is through  $R$  the  $n$ -ary relation (multidimensionality) as illustrated in Figs. 4a and 4b.

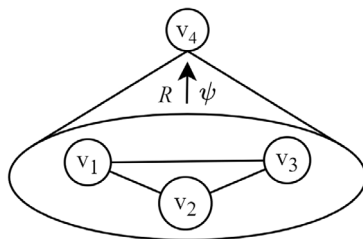


Fig. 4a. Cone representation of Hypersimplex notation  $\langle a, b, c; R; \psi \rangle$ .

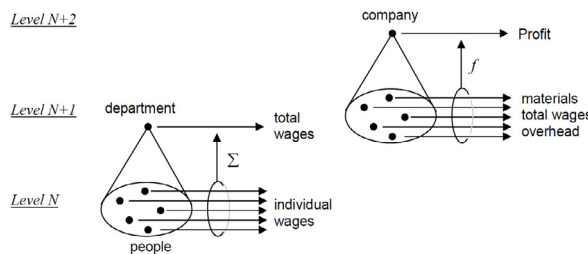


Fig. 4b. Multidimensional traffic [13].

In addition to the physical structure, HT also allows mathematical models to be created or even merged into the same model. The numerical aspects of HT are known as traffic [13] and they represent the values that flow across the system.

Johnson [13,16] discusses the need for traffic and introduces an equivalent to  $R - \psi$ .  $\psi$  takes the values from the parts and calculates a whole value which can then form a part of one or more wholes. This allows the result of one vertex to be the input to more than one whole.

The Hn model is used by SEMS to choreograph the data collection, forecasting and optimisation. The bottom level vertices are predominantly a representation of the sensors, meters and possibly other external sources, such as weather or CO<sub>2</sub> forecasts, which in turn feed the next level up. The vertex does not care about the recipient whole, or indeed have any knowledge about the whole(s) of which it is a part. However, the whole does need to know what traffic its parts are creating as this is specified by the Hn.

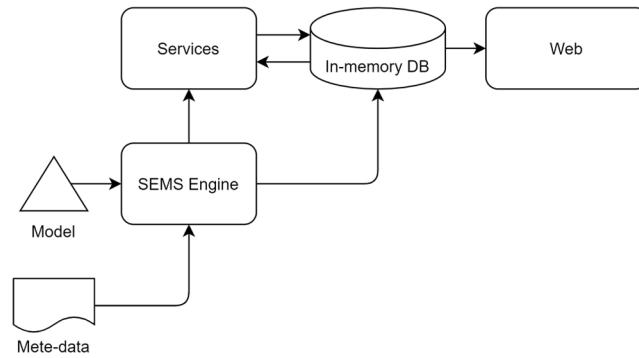
### 3.2. Application architecture

The application architecture for SEMS is illustrated in Fig. 5a. There are four main components SEMS Engine, services, in-memory database (DB), and web. In addition to the components there are two forms of configuration, the first is the Hn model used to describe the site, its assets – PV, EV, HP, etc. – and the traffic required to perform actions, such as, forecasting and optimisation. The second supports the first by providing the meta-data used to specify the parameters, such as size, Coefficient of Performance, efficiency, etc. of the specific physical asset or logical vertex used in performing the forecasting or optimisation.

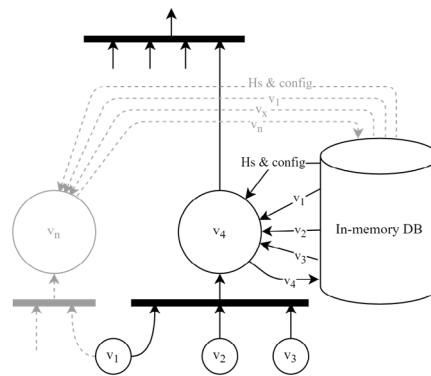
Essentially each vertex represents a specific asset on site and is named as such. However, each vertex can include the  $\psi$  function that performs the action itself. This means the SEMS can reuse common  $\psi$  functions by tailoring them to the specifics of the asset. In this architecture it was decided that each  $\psi$  function be implemented as a web-service, therefore decoupling the choreography from the data and individual function.

The SEMS engine periodically executes the model by calling each service concurrently based on the Hn model. The first level of vertices executes when SEMS is started, but vertices at subsequent levels wait for all their parts, specified as a simplex, to complete before executing, as illustrated by the bar in Fig. 5b. This means that all vertices can execute in parallel unless they are waiting for all parts to complete. Once all parts have completed the waiting vertex collects the data produced by the parts from the in-memory DB where it is stored it.

Once completed the vertex then stores its data in the in-memory DB, releases, and returns a completed status back to the SEMS engine so it can continue with the next levels until there are no more.



**Fig. 5a.** Application architecture used for SEMS;



**Fig. 5b.** SEMS software architecture illustrating HT.

### 3.3. Microservice structure

The multi-energy system software developed as part of the Sharing Cities project is composed of numerous microservices, or vertices. Fig. 6 illustrates these services and their interaction. Each service either gets and integrates data, generates predictive forecasts, runs an optimisation or interprets a control signal for the optimal operation of the system. By compartmentalising subtasks (see Fig. 6), they can be more easily modified, removed, or added which enhances the scalability of the software. Additionally, this distributed architecture is more easily tested and can be more flexibly run.

### 3.4. Optimisation & interpretation

The Pyomo package is used to formulate, solve, and analyse the structured optimisation model with GNU Linear Programming Kit (GLPK) [20] and Gurobi [21] stand-alone solvers.

The model objective is to minimise scaled, weighted values for total operational greenhouse gas emissions and/or cost. Model constraint are based on equipment operating limits, and heat-power systems balancing. Additionally, constraining the model meant substation capacity limits were not breached, in turn, deferring costly electricity grid infrastructure upgrades.

Outputs include 24-hour profiles for energy asset power inputs and/or outputs as well as energy storage levels. These profiles are interpreted into BMS control signals (see Fig. 6) for equipment scheduling and storage

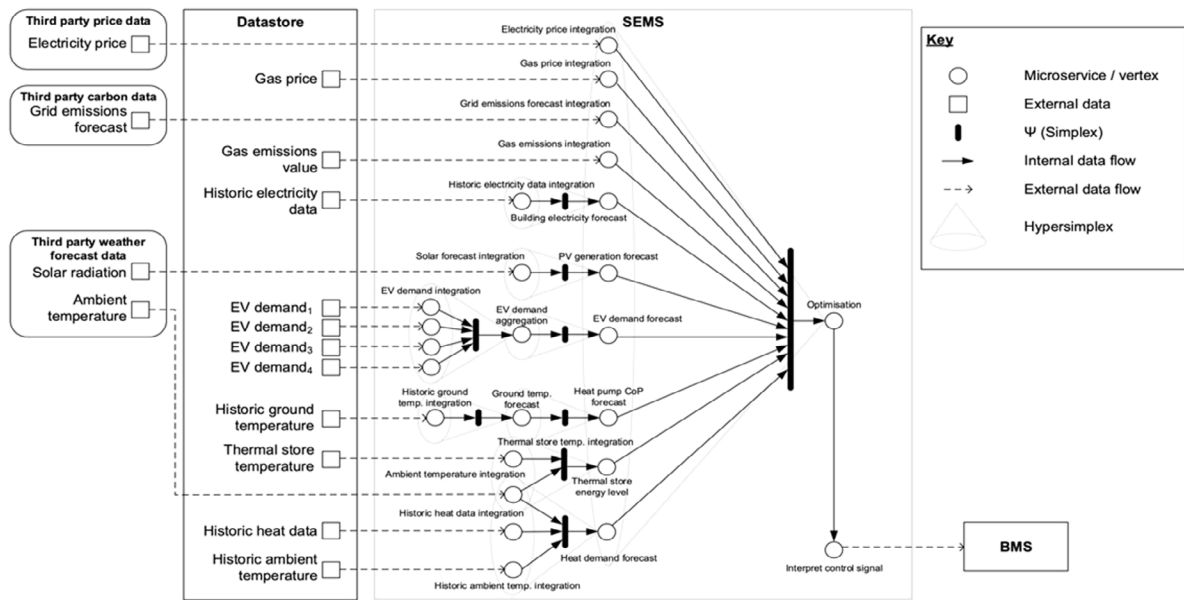


Fig. 6. SEMS microservices/vertices, simplices and data flows.

charge/discharge/bypass commands using setpoints. The BMS, acting as an intermediary between the SEMS and assets on site, is responsible for communicating control signals.

The software components: SEMS engine, services and in-memory DB (see Fig. 5a), are containerised and deployed using Docker to an AWS EC2 server for flexibility.

## 4. Results

### 4.1. Heat demand forecast

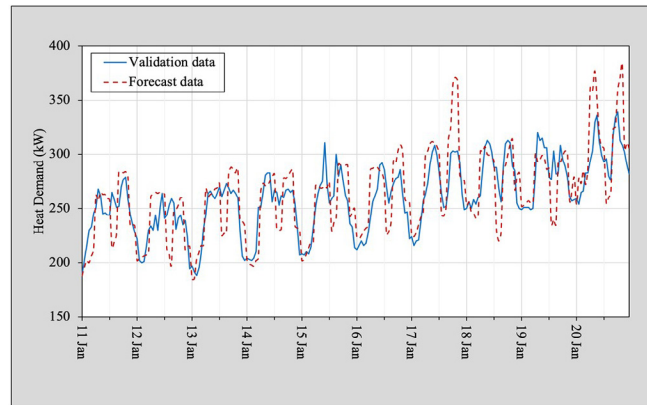
Heat demand is forecast using a multivariate regression model after testing of other commonly cited algorithms. These included artificial neural network, support vector machines which showed low accuracy. The regression result gave an R2 score of 0.80–0.85 showing the predicted value is close to the simulated heat demand value. Moreover, in real terms the root mean square error was 33.61 which means the predicted to simulated value differed by around 34 kW using month, weekday, hour and outdoor temperature variables. Examples of the predicted and simulated heat demand can be seen in Fig. 7. The three-year dataset was divided into two years for training and one year for validating the model.

### 4.2. Electricity demand forecast

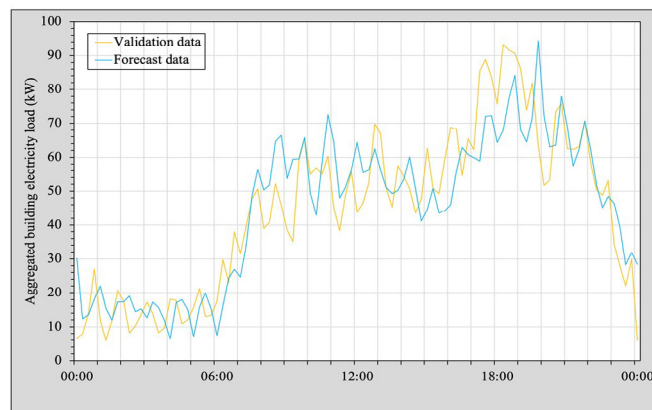
The whole building electricity demand is forecast using a seasonal autoregressive integrated moving average model. This model was chosen as it can be used for univariate time series data forecasting where there is trend and seasonality [22,23]. The model is trained on three years of historic data and then validated against a further year. Examples of the results can be seen in Fig. 8 which shows a typical winter day. Both validation and forecast data are relatively well matched due to the consistency of daily residential electrical load trends and seasonality.

The model achieved a root mean square error of 10.652. This means that on average, the model was wrong by about 10.7 kW for each prediction made. This is considered a reasonable error and can be accounted for in the energy optimisation logic. Root mean square error is the standard deviation of the prediction errors and so is a way to measure how far from the regression line true data is.





**Fig. 7.** Example heat demand forecast values (red dashed) vs simulated demand/validation dataset (blue) for 10 days in winter.



**Fig. 8.** Example aggregated domestic electricity demand profile for a typical summers day, comparing validation and forecast data.

## 5. Discussion & Conclusions

The minimum viable software product presented in this paper was created for implementation at the Ernest Dence estate in Greenwich, London. The estate acts as a case study of a system requiring high level control due to the complexities of increasingly interlinking energy vectors and associated constraints.

The software application has a number of commercial and environmental benefits including, reduced operational emissions and cost, energy balancing for the optimal use of assets, and preventing or deferring reinforcement costs of network infrastructure driven by the electrification of heat and transport. Despite the design focus on a heat and power system, the project specifications focused on scalability, flexibility and replicability to ensure that future software applications and development are not limited. The Hn provides a simple way to create a multilevel structure that groups the inputs and parameters to form discrete calculations with outputs for use at the next level, or to form parts of a number of calculations. The microservices enable the separation of concerns between the controller, data and the calculator, whilst providing the discrete functional units at scale.

There is an ambition to use the SEMS for different energy optimisation problems. For example, the management of an eBus smart charging depot including a consideration of battery capacity, live bus route tracking and scheduling. New case studies and associated algorithm development will be done on a project-by-project basis. However, there are a number of improvements planned for the 22 services in the current version. For the two example services presented in this paper – heat and electricity demand forecasting – alternative machine learning algorithms will be



tested including Long Short-Term Memory which has proven effective, when dealing with other time series data due to its capability to retain useful and forget useless information.

As well as code development, future work will focus on using data from meters and sensors connected to a physical system. Currently the parameterisation of predictive algorithms is done statically based on patterns in years of historic data, the use of live data will allow for this to be done dynamically improving accuracy and adaptability. Equally, with the ability to compare forecast and simulated profiles we can auto-modify predictions in line with anomalous or unexpected data.

The current design is a foundation from which to build the capability of the SEMS software, diversify its functions and applications. A further paper will present the results of the physical system integration and operational performance at the Ernest Dence estate.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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