Optimization of carbon emissions in smart grids

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Outline

1. Problem statement
2. Electrical power system
3. Carbon footprints
4. Methodology
   (a) Ensemble Kalman Filter (EnKF)
   (b) Ensemble Close-Loop Optimisation (EnOpt)
6. Results
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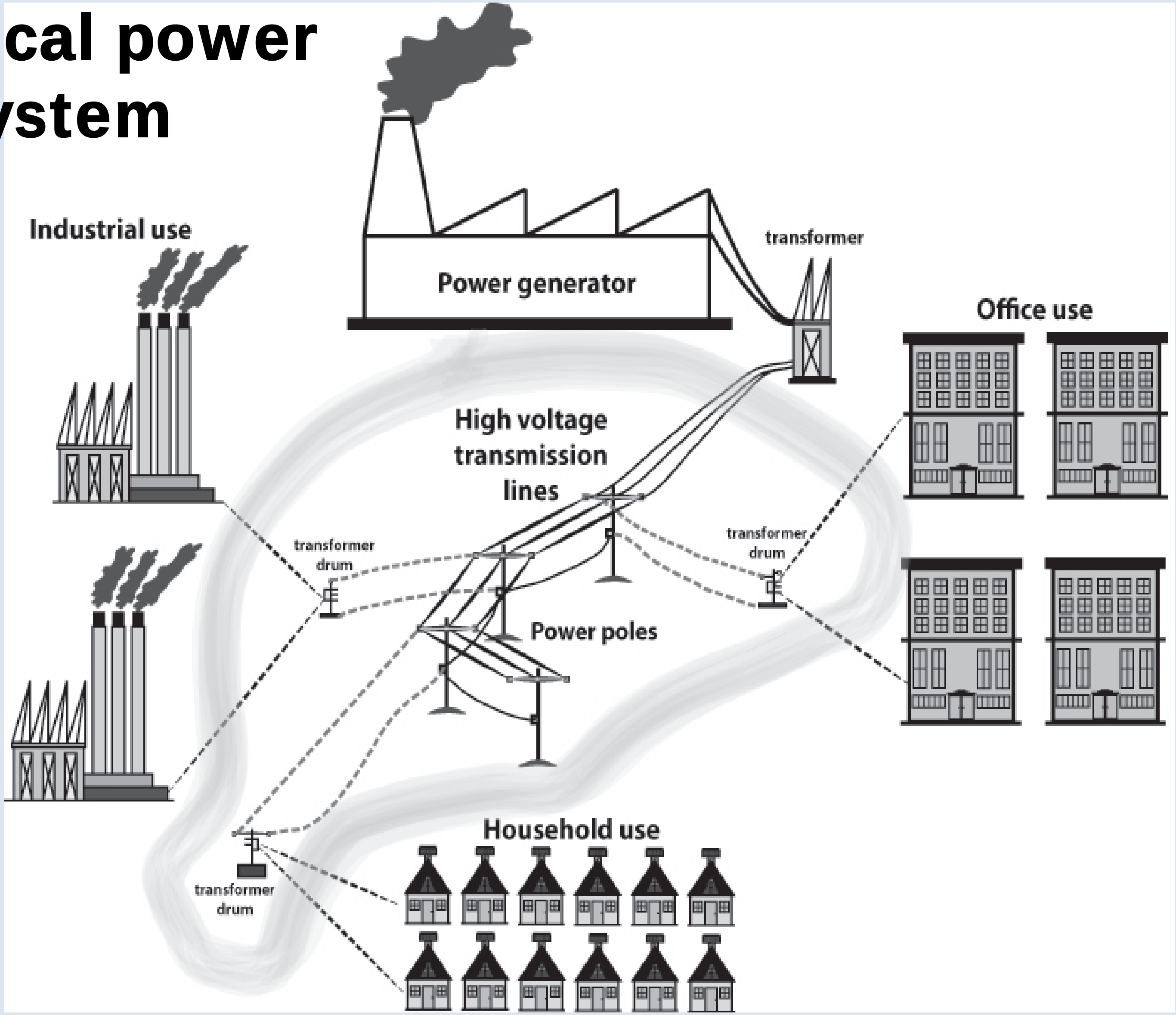
Problem statement:

Minimisation of carbon emissions (gCO_2eq) with suitable control settings in electrical systems.

Estimation of uncertainties.

Electrical power system



Lau et. al., ECM 2014

Electrical signal - periodicities

1. Generated time series should have daily and annual periodicities.

2. The electrical voltage can be expressed into state space, with seasonal cycle, combined with annual and diurnal cycle and noises.

$$X_k(t) = \underbrace{\boxed{S\left(\frac{t}{T_1}\right)}}_{\text{Annual Cycle}} + \underbrace{\boxed{D\left(\frac{t}{T_2}\right)}}_{\text{Diurnal Cycle}} + \underbrace{\varepsilon}_{\text{Signal noise}}$$

Carbon footprints

1. Reported in kilograms (or grams) of carbon dioxide CO_2 equivalent per unit of energy (kWh) – $kgCO_2/kWh$.

2. Calculated by: Ricardo – AEA, an UK research company.

Carbon factors in UK electricity generation

Types of Fuel	Carbon footprints (gCO_2eq/kWh)
Coal	788-899
Oil	600-699
Open cycle gas turbine (OGCT)	466-586
Combined cycle gas turbine (CCGT)	367-487
Wind	20-94
Nuclear	20-26
Hydro	2-13

UK variable electricity grid carbon factor

Estimation of UK electricity grid carbon factors:

$$EGCF(t) = \frac{\sum_{t=1}^{T} \sum_{k=1}^{K} (C_k \times E_k(t))}{\sum_{t=1}^{T} E_k(t)}$$

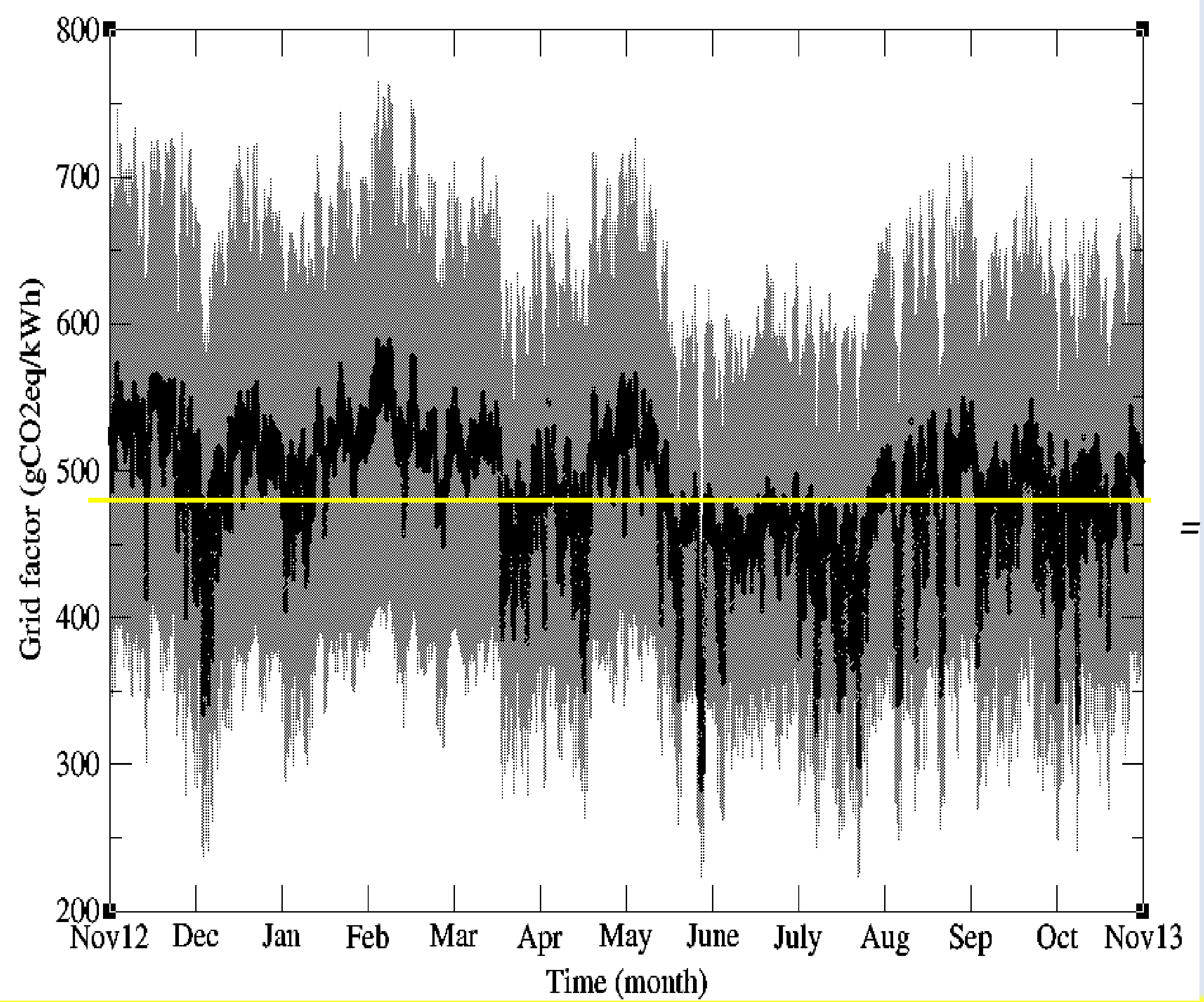
Where,

C_k - Carbon footprints for different fuels (gCO_2eq/kwh)

E_k - The energy generated (kWh)

t - Time index, k- Fuel type index

UK electricity grid carbon factor with uncertainties



Average EGCF
= 493.85 gCO_2eq/kWh

Data courtesy of Balancing Mechanism Reporting System (BMRS).

Carbon emissions

The product of activity data and the carbon footprints.

$$Emissions(t) = Energy(t) \times Carbon\_footprints(t)$$

Units = $kgCO_2eq$

Carbon savings

The difference between the emissions (BAS) and the innovations employed.

$$Carbon\_savings(t) = Emissions_{BAS}(t) - Emissions_{IMPROVED}(t)$$

Units = $kgCO_2eq$

Methodology for carbon emissions and savings

1. Ensemble Kalman Filter (EnKF) for ensemble estimation of grid state and the associated uncertainties.

2. Ensemble Close-Loop Optimisation (EnOpt) for maximisation of carbon savings.

EnKF

1. Ensemble realizations - model state and state updates.

2. Adjust an ensemble of the model to be consistent with real-time production data.

EnKF - general formulations

Collect variable of interests in grid state vector '*y*'

$$y = \begin{bmatrix} m \\ d \end{bmatrix}$$

Where,

m=state variables (e.g., working families, pensioners, industrials, offices)

d=observation variables (energy production and consumption data, carbon emissions)

EnKF - Ensembles

State vector y consists of energy usages corresponds to various consumers:

$$y = [Type_1, Type_2, Type_3, \cdots, Type_N]^T$$

Ensemble of state vector y is denoted in Matrix '*Y*':

$$Y = [y_1, y_2, y_3, \cdots, y_{Ne}]$$

Where *N = Total number of variables;* N*e*=*Total number of ensembles*

EnKF – Ensemble updates

Apply EnKF to propagate the ensemble to obtain forecasted ensemble:

$$y_i^u = y_i^p + C_Y H^T (H C_Y H^T + R)^{-1} (d_{obs,i} - H y_i^p)$$

Where,

y^u=updated state

y^p=predicted state

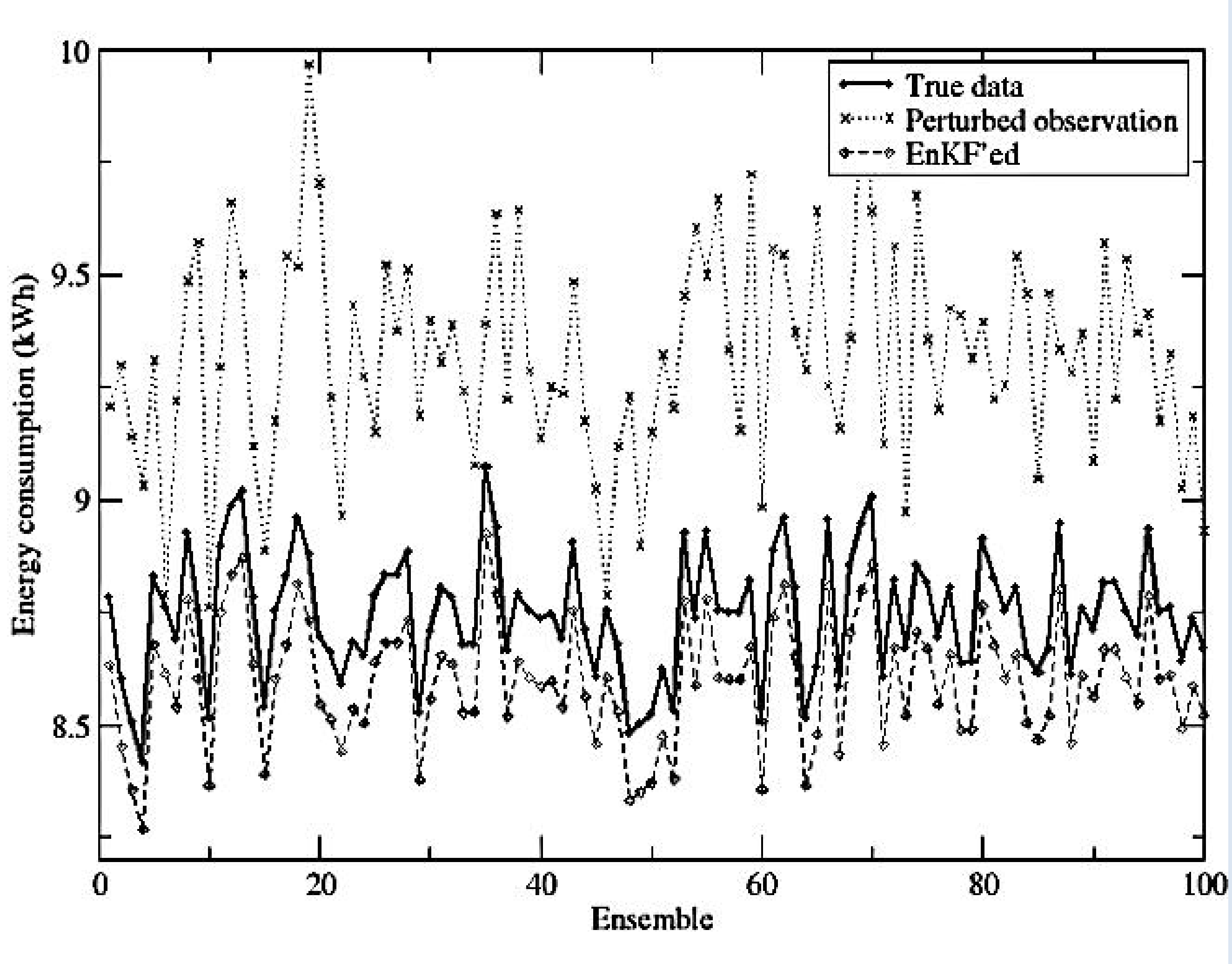
C_Y=covariance matrix of state vector y

H=measurement operator relating the model state to the observation variables d

R=covariance matrix of the measurement error (positive definite)

d=perturbed observations

EnKF – Artificial data of energy consumption



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NPL National Physical Laboratory

Ensemble-based close-loop production optimisation (EnOpt)

1. Search direction used in the optimization is approximated by an ensemble.

3. Combined with EnKF to reduce the uncertainty of the model.

4. Sequential updating method - updated parameters are to be consistent with the energy production data in time.

5. Optimises both control settings *x* and expectation of the objective function *f*.

(Chen at al., SPE, 2008)

EnOpt – Control variables

Ensemble of control variables '*x*' is created:

$$x = [x_1, x_2, x_3, \cdots, x_{Nx}]$$

Where

N_x=Total number of control variables
x = energy data (generator properties, controlled generation, consumption, consumer usage behaviour)

EnOpt – ensembles

1. Ensemble of *grid state vector* ***y*** :

   - *resultant energy generation, consumption and carbon emissions.*

2. Ensemble of *controlled variables* ***x***:

   - *generator properties, controlled generation, consumption, consumer usage behaviour.*

EnOpt – ensembles

Ensemble x acts as the controller that integrates with *Ensemble y* in controlling energy generations and consumptions.

EnOpt – Objective function

Objective function = carbon emissions *(gCO_2eq)*:

$$f(x,y) = \sum_{i=1}^{N_t} EGCF_i \times E_i(x,y)$$

Where,

N_t=*total number of time steps*

E_i=*Energy consumptions (kWh)*

$EGCF_i$=*Electricity Grid Carbon Footprints*

x=control variables

y=grid state vector

EnOpt – Steepest descent

Optimise control variable *x:*

$$x_{\lambda+1} = \frac{1}{\alpha} C_x C_{x,f_{\boldsymbol{Y}}(x)} - x_\lambda$$

Where,

λ =*iteration index*

C_x=*covariance matrix of control variable x*

$C_{x,f_Y(x)}$=*cross covariance between control variables x and* $f_{\boldsymbol{Y}}(x)$

α=*tuning parameter*

EnOpt

Cross-covariance:

$$C_{x,f_{\boldsymbol{Y}}(x)} = \frac{1}{N_e - 1}\sum_{i=1}^{N_e}(x_{\lambda,i} - \overline{x_\lambda})\left(f\left(x_{\lambda,i}, y_i\right) - \overline{f(x_\lambda, y)}\right)$$

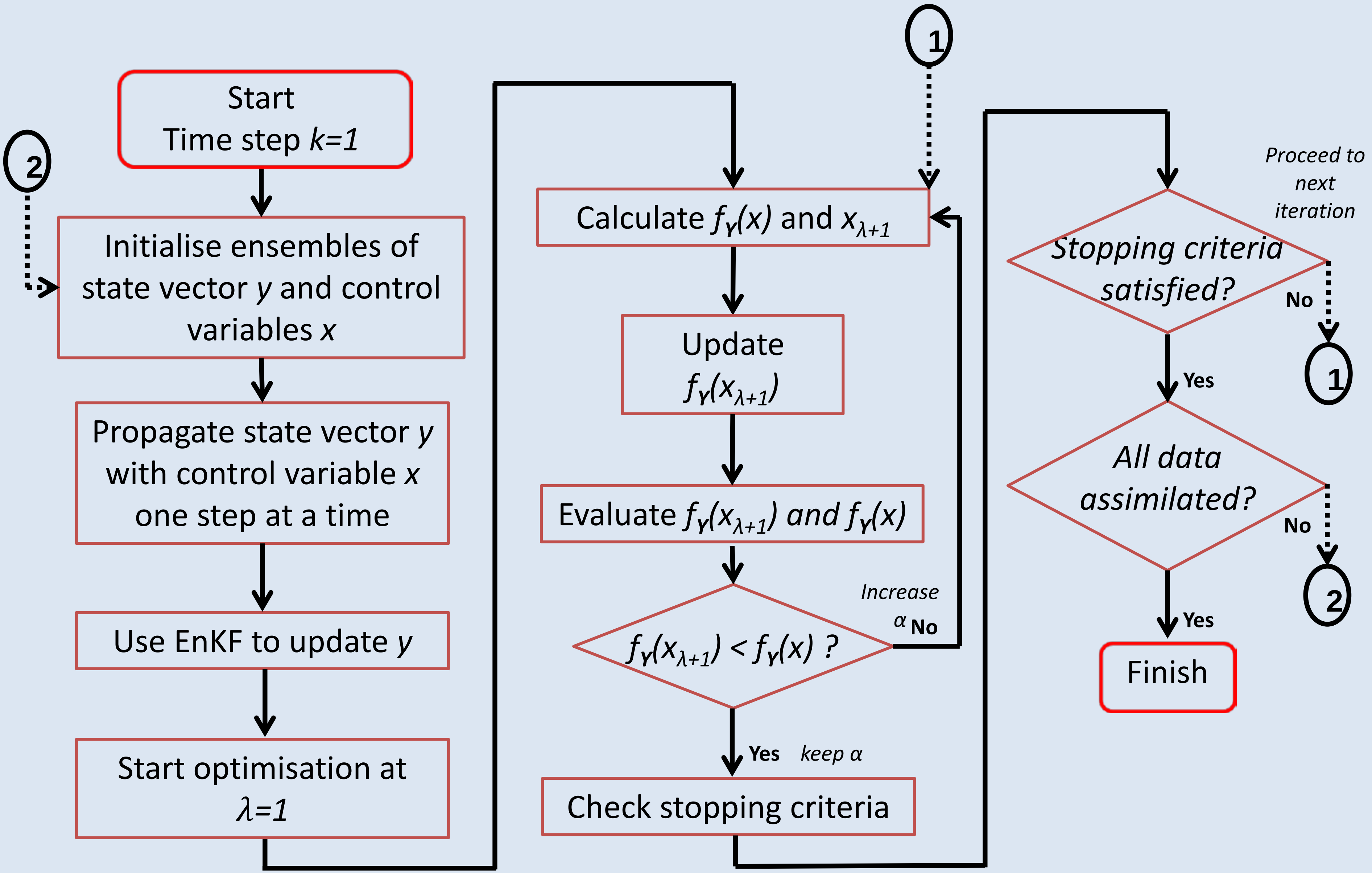
Where,

$\overline{x_\lambda}$=*mean of control variables x*

$\overline{f(x_\lambda, y)}$=*mean of the objective function f*

N_e=*Total number of ensembles*

λ =*iteration index*



Start
Time step $k=1$
Initialise ensembles of state vector y and control variables x
Propagate state vector y with control variable x one step at a time
Use EnKF to update y
Start optimisation at $\lambda=1$
Calculate $f_Y(x)$ and $x_{\lambda+1}$
Update $f_Y(x_{\lambda+1})$
Evaluate $f_Y(x_{\lambda+1})$ and $f_Y(x)$
$f_Y(x_{\lambda+1}) < f_Y(x)$?
Increase α
No
Yes
keep α
Check stopping criteria
Stopping criteria satisfied?
Proceed to next iteration
No
Yes
All data assimilated?
No
Yes
Finish
1
2
1
2

EnOpt – Stopping criteria

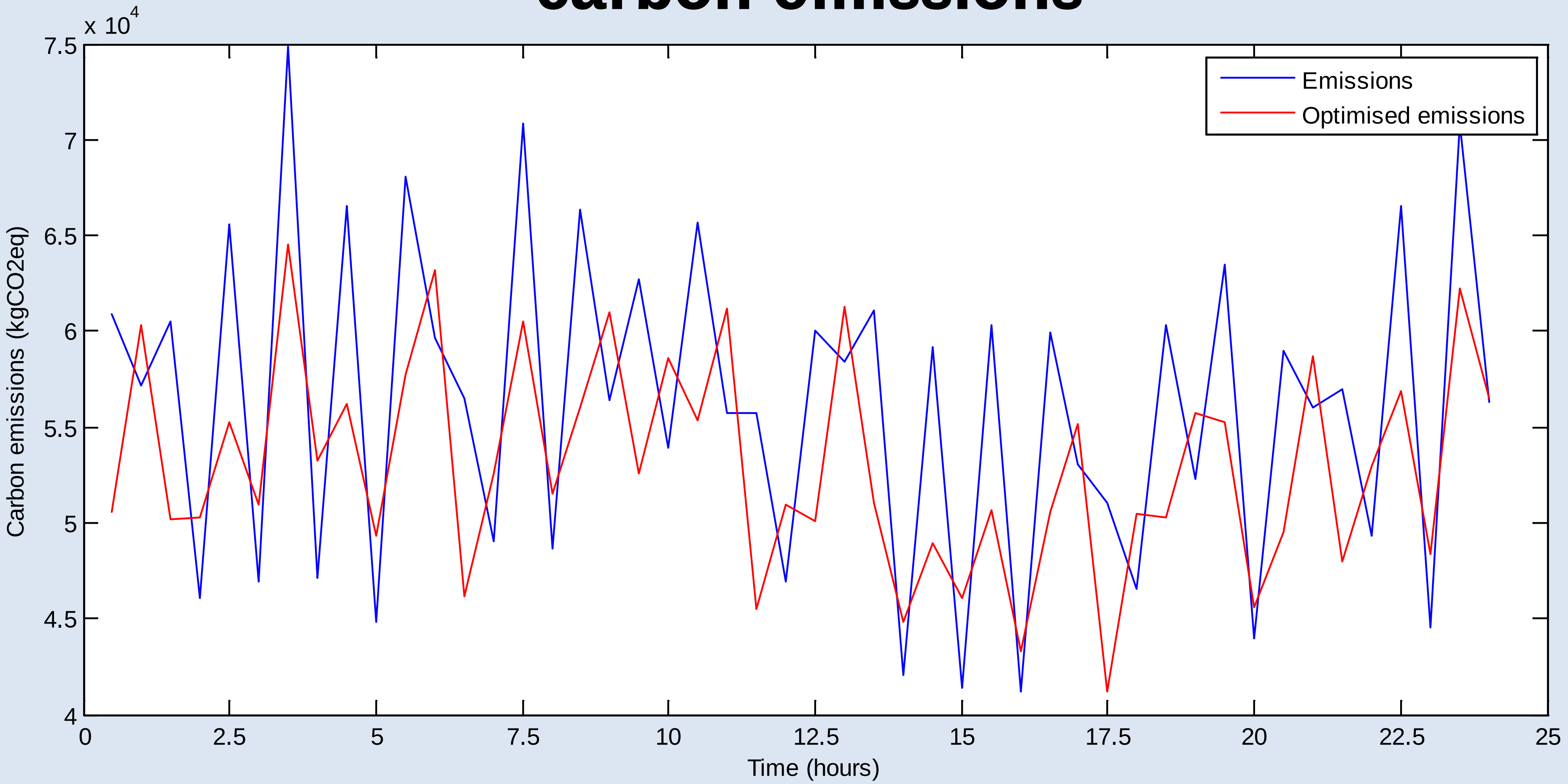
1. Maximum optimisation step λ_{max}.
2. Unsuccessful search for tuning parameter α.
3. The relative increase of the objective function $f_{\gamma}(x)$ is less than 1 percent.
4. Not allowed to increase α more than twice.

Ensemble

Consumers and generators considered:

	Quantity
Restaurant	10
Pensioner	20
Office/retailer	10
Industrial	5
School/university/college	5
Working Family	50
Green Generator	2
Non-green Generator	3

EnOpt – Artificial data of usual vs. optimised carbon emissions



Carbon savings (24 hrs, 105 ensembles) = 153.8 ± 4.51 tonnesCO2eq

Uncertainties

1. Carbon footprints.

2. Consumers (behavioural usage).

3. Generators (green and non-green power stations).

Future work – constrained EnOpt

1. Use of Lagrange multipliers in the steepest descend technique in determining the effect of perturbations on the optimal solution.

Given a system constraint, the new modified objective function:

$$\bar{f} = \sum_{k=1}^{K} L[y(k+1), y(k), x(k), \lambda(k+1)]$$

where *L is* Lagrangian.

(Naevdal et al., CG, 2006)

Summary of EnKF and EnOpt

1. Uncertainties are reduced through EnKF.

2. The updated ensemble estimates (EnKF'ed) are able to match with the real-time production data.

3. Through EnOpt, maximisation of carbon savings can be achieved along with optimised control variables.

Publications

1. E.T. Lau, Q. Yang, A.B. Forbes, P. Wright, V.N. Livina "Modelling carbon emissions in electrical systems", *Energy Conservation and Management*, vol. 80, no. 59, pp. 573-581, 2014.

2. E.T. Lau, Q. Yang, G.A. Taylor, A.B. Forbes, P. Wright, V. N. Livina "Optimization of carbon emissions in smart grid: a mathematic model", UPEC2014 conference proceedings (accepted).

3. E.T. Lau, Q. Yang, G.A. Taylor, A.B. Forbes, P. Wright, V.N. Livina "Carbon savings in smart interventions in electrical systems", IEEE Transactions on Smart Grid, in preparation.

Thank you!

Bibliography

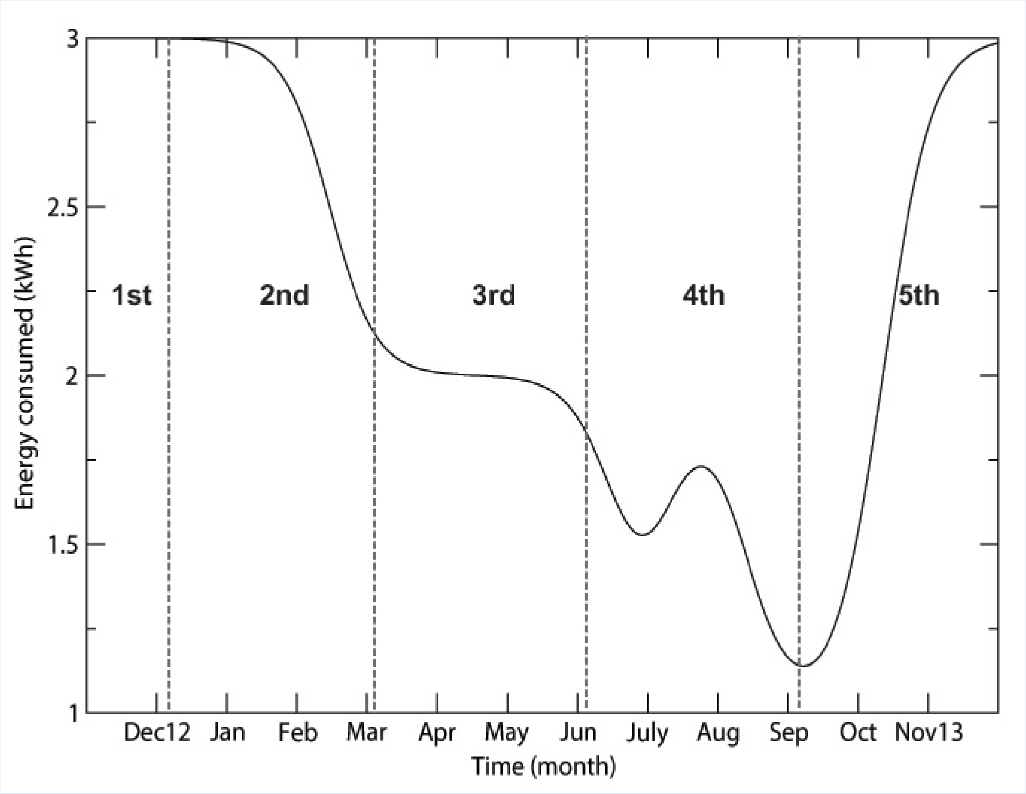
1. Energy use and behaviour change, Postnote 417, 2012.
2. BMRS data, available at: http://www.bmreports.com/
3. Efficient ensemble-based close loop production optimisation, Chen et. al, SPE, 2008.
4. Carbon footprints of electricity generation, Postnote 268, 2006 and Postnote Update 383, 2011.

Add-ons

Periodicities

Annual Cycle	Diurnal Cycle
1. Based on four seasons, with different rates of power consumptions in every season.	1. Represents one period of cycle (24 hours per cycle) 2. Cycles are continuous. 3. Based on four categories: (1) Working family; (2) Pensioner; (3) Industrial daytime office; (4) Industrial (1 shift).

Annual cycle



Where:

T_1 – 365 days

C_1 – y-axis adjustment

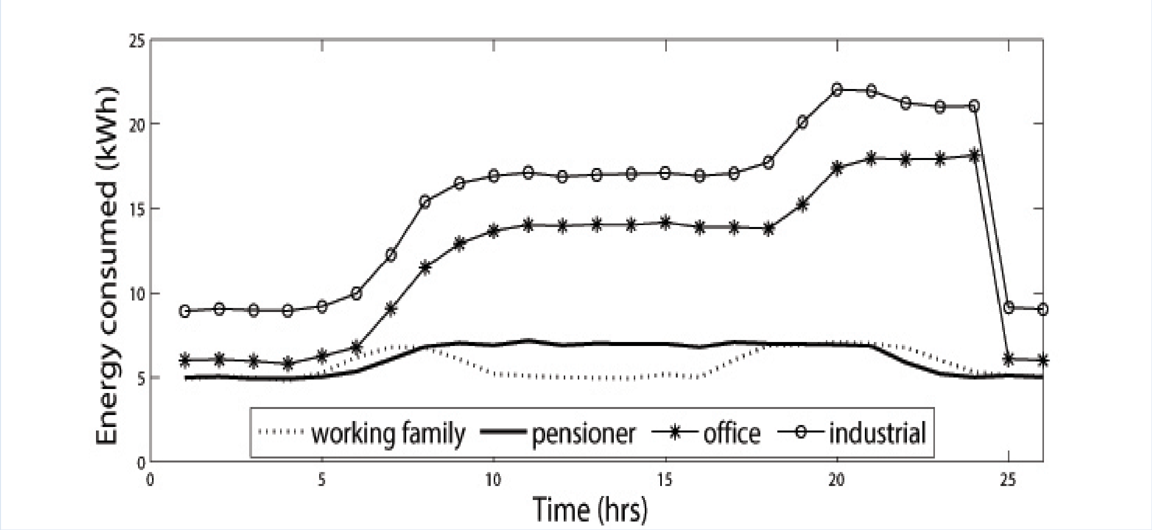
L - width of HTF

a_k - particular time interval

k-index of data subset

$$A(t) = C_1 + \sum_{k=1}^{K} \left(\tanh \frac{t - a_k - T_1(k-1)}{L} \right)$$

Diurnal cycle



Where:

T_2 – 24 hours

C_1 – y-axis adjustment

L - width of HTF

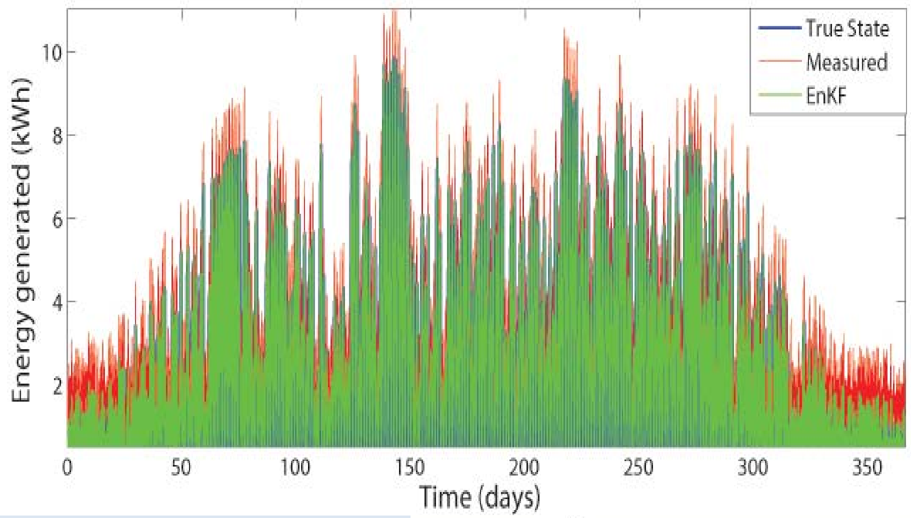
a - particular time interval

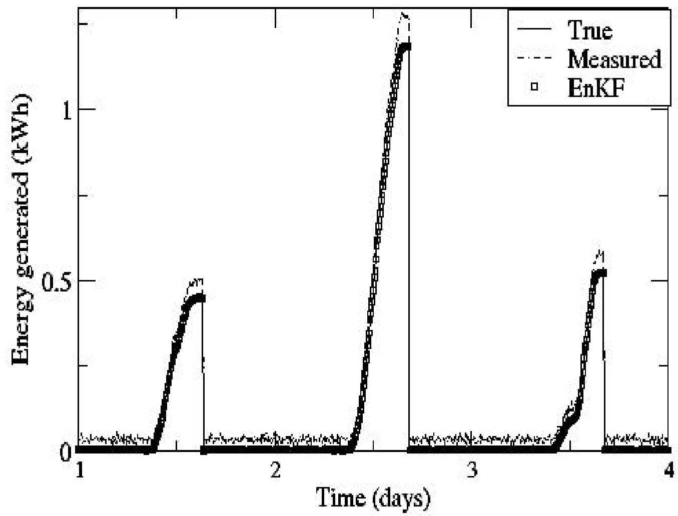
k-index of data subset

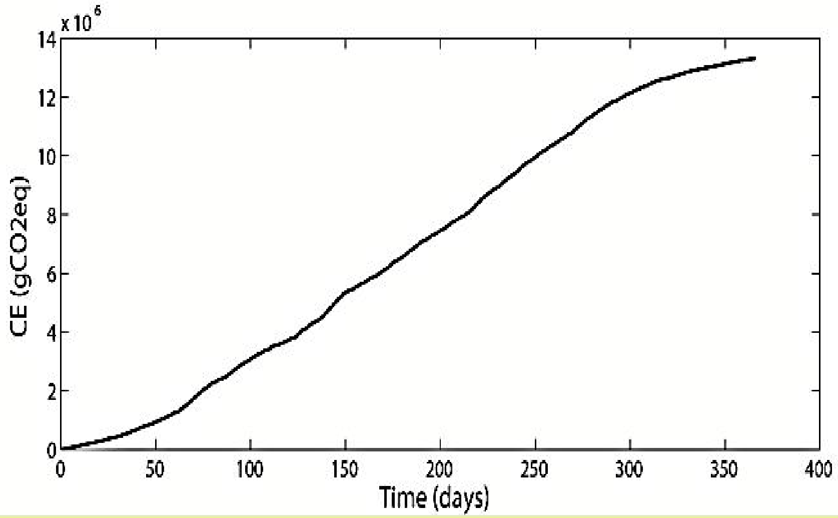
C_2 – adjustment constant at particular HTF term

$$D(t) = C_1 + \sum_{k=1}^{K} \left(C_2(k) \cdot \tanh \frac{t - a - T_2(k-1)}{L} \right)$$

Photo-voltaic data of Brunel installation







Data courtesy of Brunel University

Optimisation constraints

Constraints : $E_i^{min} \leq E_i \leq E_i^{max}$

$$\bar{E}_i \leq \sum_{i=1}^{I} E_i$$

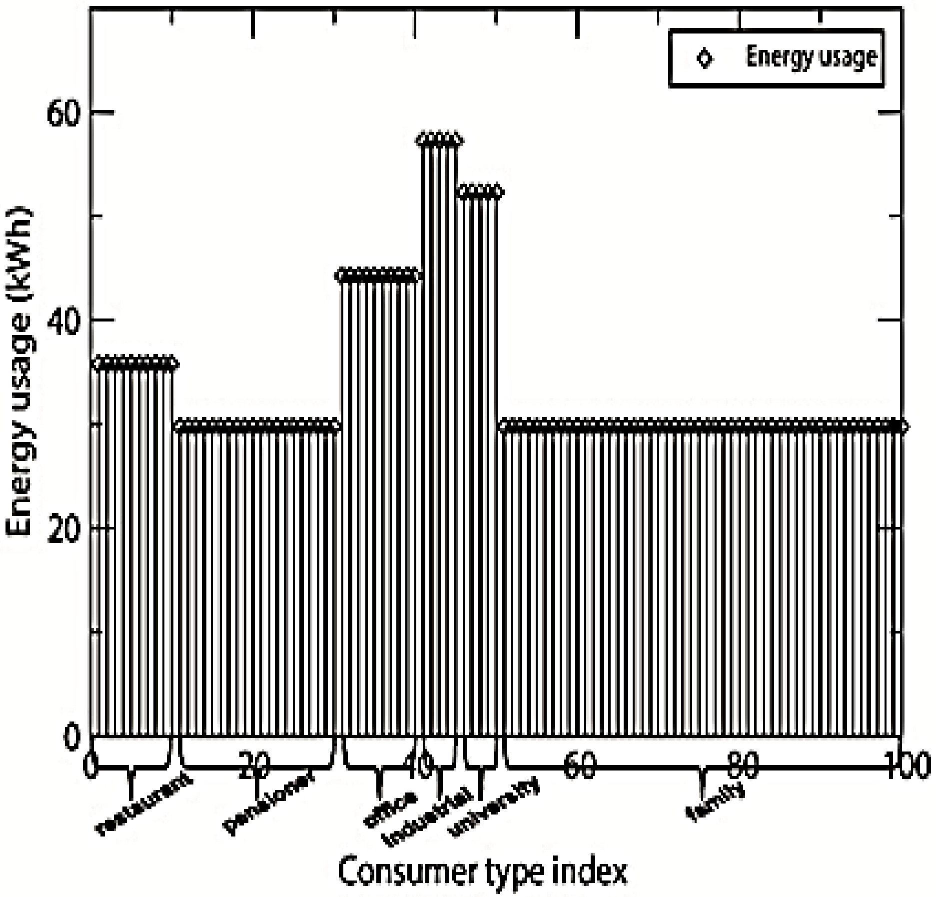
$$\sum_{i=1}^{I} E_i \geq E\_min\_demand$$

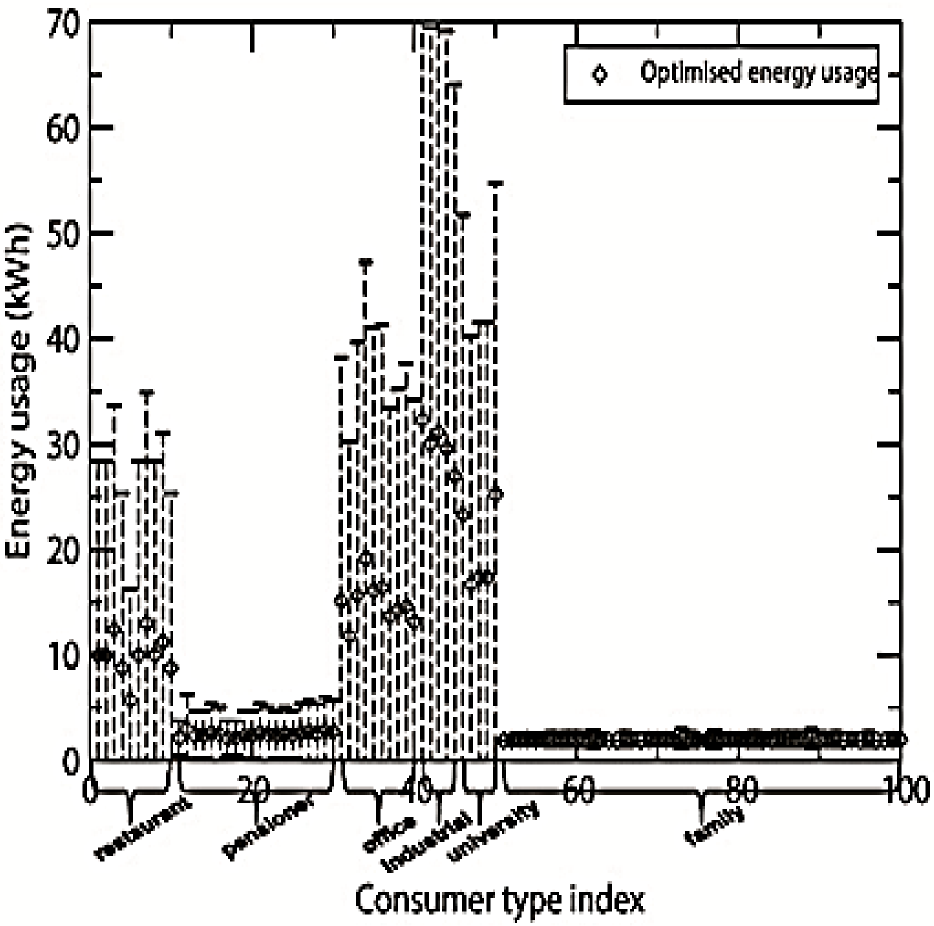
i = 1,2,3,…, I is the corresponding energy consumption of consumers

Optimisation constraints - results

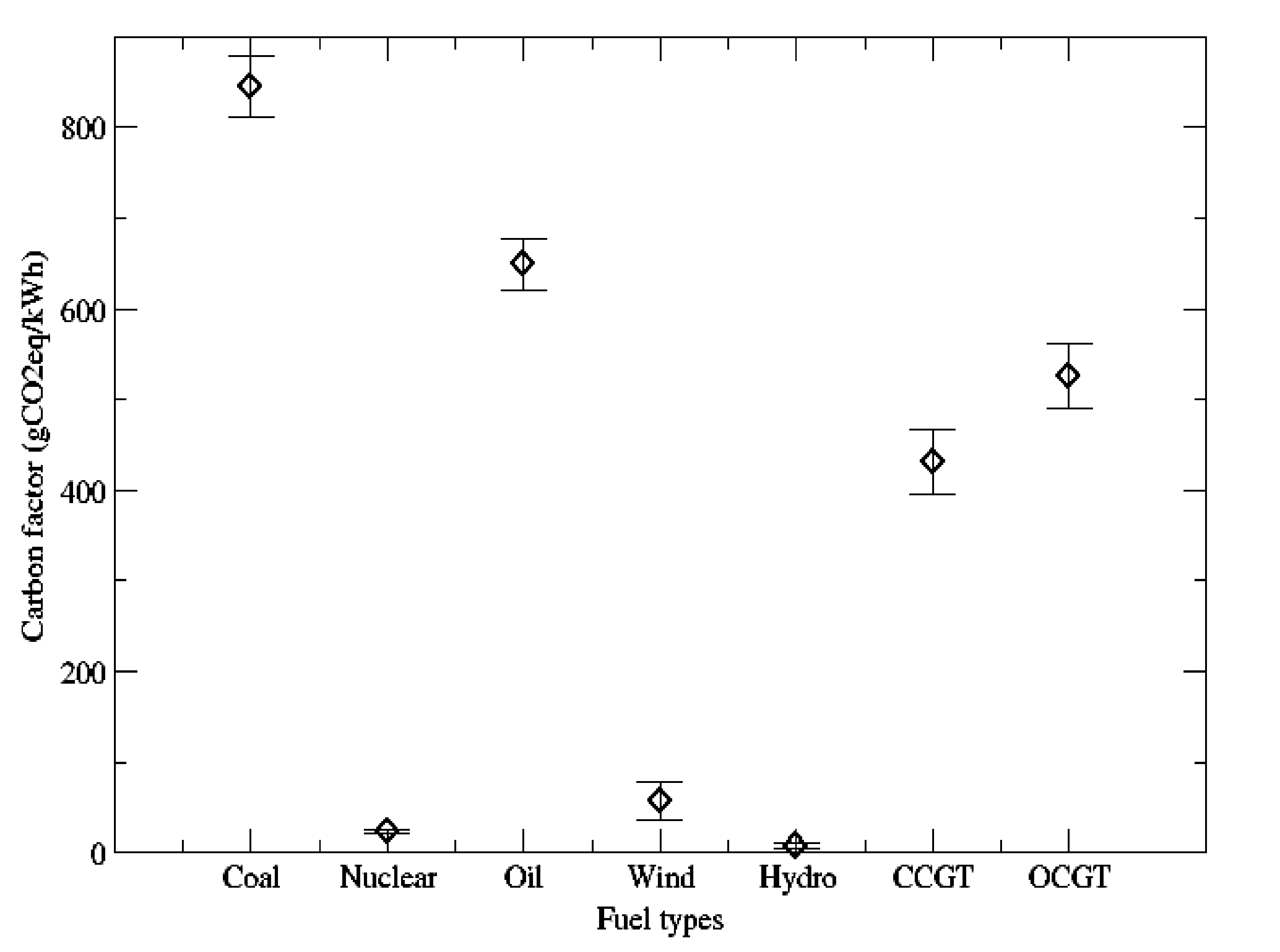
◇ Optimised energy consumption

Error bars

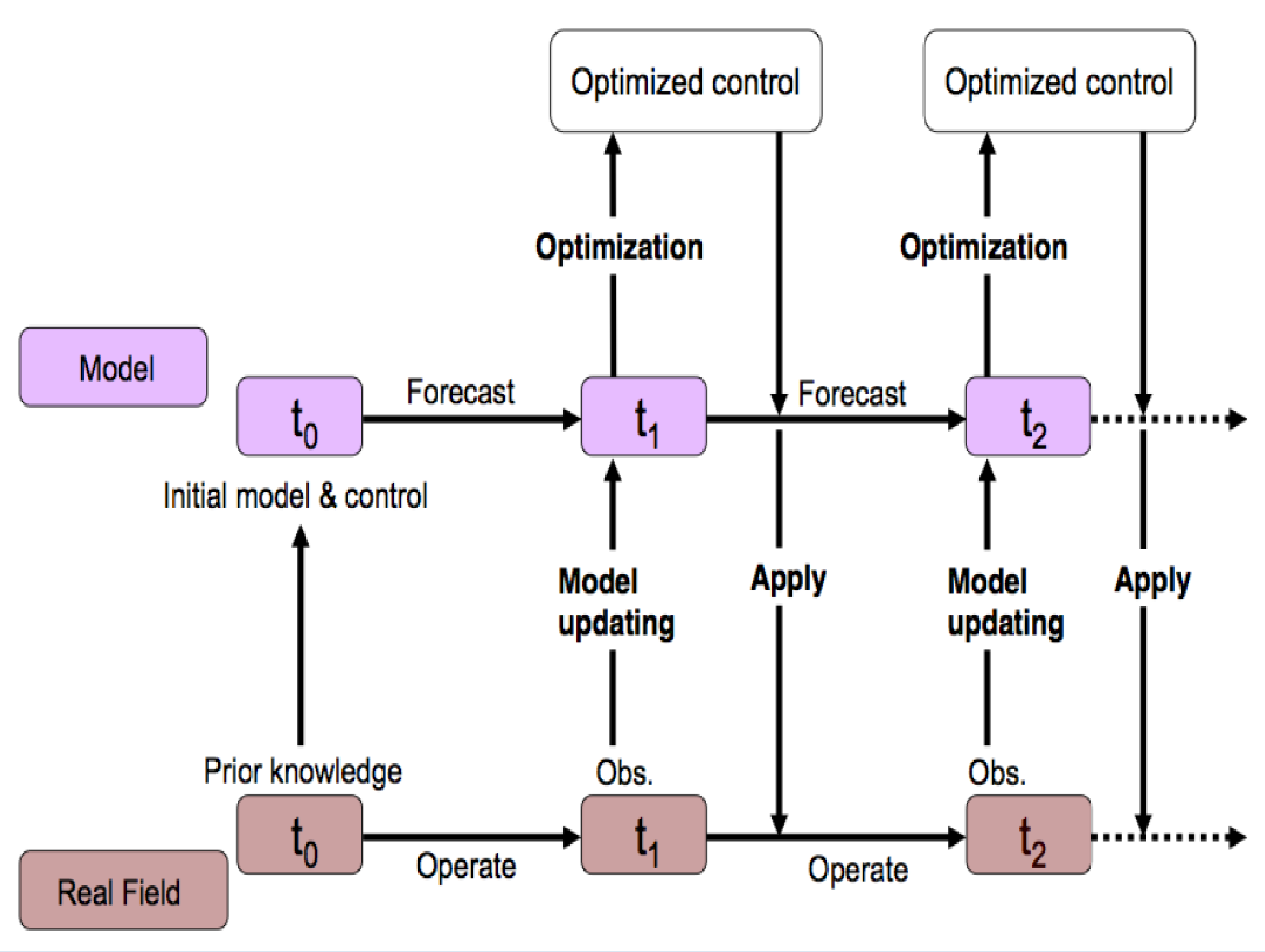




UK Carbon footprints with uncertainties



EnOpt (EnKF + optimisation)



Source: Chen et. al (2008) EnOpt, SPE.