Model predictive control of non-domestic heating using genetic

programming dynamic models

Tiantian Dou a, Yuri Kaszubowski Lopes a, Peter Rockett a,∗, Elizabeth A. Hathway b,

Esmail Saber b,1

a Department of Electronic and Electrical Engineering, University of Sheffield, Mappin Street, Sheffield S1 3JD, UK

b Department of Civil and Structural Engineering, University of Sheffield, Mappin Street, Sheffield S1 3JD, UK

∗ Corresponding author.

E-mail address: p.rockett@shef.ac.uk (P. Rockett).

1 Current address: Civil & Building Services Engineering Division, School of

the Built Environment and Architecture, London South Bank University, London

SE1 0AA, UK.

Keywords:

Genetic programming

Dynamic non-linear system identification

Model predictive control

Building energy management

a b s t r a c t

We present a novel approach to obtaining dynamic nonlinear models using genetic programming (GP)

for the model predictive control (MPC) of the indoor temperatures of buildings. Currently, the largescale

adoption of MPC in buildings is economically unviable due to the time and cost involved in

the design and tuning of predictive models by expert control engineers. We show that GP is able to

automate this process, and have performed open-loop system identification over the data produced by

an industry grade building simulator. The simulated building was subject to an amplitude modulated

pseudo-random binary sequence (APRBS), which allows the collected data to be sufficiently informative

to capture the underlying system dynamics under relevant operating conditions.

In this initial report, we detail how we employed GP to construct the predictive model for MPC for

heating a single-zone building in simulation, and report results of using this model for controlling the

internal environmental conditions of the simulated single-zone building. We conclude that GP shows

great promise for producing models that allow the MPC of building to achieve the desired temperature

band in a single zone space.

1. Introduction

Model predictive control (MPC) [1] is a powerful control

methodology well-suited to systems in which there is an appreciable

delay between an input being applied and any observable

response, and which may also have control constraints; large

(non-domestic) buildings are among such systems. Central to

MPC is a predictive model of the dynamics of the system being

controlled. Given a prediction horizon extending some number

of discrete time steps into the future, the controller optimises

the sequence of future inputs by minimising some objective

function. Typically, this objective comprises a weighted sum over

the prediction horizon of the deviations from a desired setpoint

together with the control effort, the magnitudes of the control

changes. This latter term is designed to penalise rapid switching

of the input and hence minimise actuator wear. At every time

step, the future input sequence is optimised, the first of this input

sequence applied to the system and the whole process repeated

at the next time step. This forever advancing prediction interval

gives the technique its alternative name of receding horizon

control.

Although MPC has been widely employed in the chemical

process industries, where it had its origins, applications to buildings

are currently only at the research stage — see, for example,

Rockett and Hathway [2] for a review. Critical to MPC, whatever

its domain of application, is the performance of the predictive

model.

The generally superior climate control of MPC in buildings

compared to conventional rule-based approaches appears to offer

the potential for significant energy savings – maybe up to

25% [2] – and makes buildings MPC worth pursuing in order

to reduce CO2 emissions and to improve internal environmental

quality. However, at a round table discussion at a workshop on

MPC in buildings held in Montréal in 2011, Henze [3] noted

attendees estimated 70% of total costs for MPC implementation

were consumed by the creation and calibration of the predictive

model that lies at the heart of MPC. In fact, this figure

agrees with the 75% often quoted by the wider process-control

community [4]. Traditionally, such models are produced by extensive

fine-tuning by highly skilled control engineers. Although

the high cost of predictive model creation may be tolerable in the

highly-capital intensive environment of petrochemicals, Rockett

and Hathway [2] have pointed out that such high costs currently

make MPC economically unviable for the control of buildings. It is,

therefore, critical for the economic uptake of MPC in buildings to

create predictive models of the system dynamics using machine

learning-based methods that can learn from data obtained from

the building in operation rather than be hand-crafted by experts.

Further, the characteristics of buildings change over time, either

due to changes in use, internal alterations, or indeed external

factors, such as the erection/demolition of adjacent buildings

that change the solar gains or façade wind pressures on the

building under control. Such changes will change the dynamics

of the building and necessitate a recalibration of the predictive

model in order to maintain optimised control. Rapid and low-cost

recalibration without human intervention is thus also essential to

maximise the ongoing benefits of MPC in buildings.

Buildings are widely acknowledged to exhibit non-linear dynamics

and therefore require a non-linear predictive model. For

example, in the situation described in the present paper (see Section

3.2), the heat transfer from a conventional hydronic radiator

to the room space is non-linear [5,6]; the solar energy entering

a building via a window was found to be non-linear function

of incident radiation by Sturzenegger et al. [7]. The problem of

formulating a non-linear predictive model has been discussed in a

seminal paper by Sjöberg et al. [8]. Assuming sampling at discrete,

equally-spaced time steps, the one-step-ahead (OSA) prediction

ˆyk+1 of a dynamical system at time (k + 1) is given by:

ˆyk+1 = f (uk, uk−1, . . . , uk−n, yk, yk−1, . . . , yk−m) (1)

where u is a vector of inputs, or so-called exogenous variables.

The problem is to identify i) f , the non-linear function, (ii) the

value of n dictating how many of the previous inputs need to be

considered, and (iii) the value of m, the number of previous (autoregressive)

outputs to be included. The sets of delayed variables

{uk, uk−1, . . . , uk−n} and {yk, yk−1, . . . , yk−m} are usually termed

lag sets and compactly incorporate the ‘inertia’ of the controlled

system. To implement MPC we generally need a model that

produces a set of accurate future predictions over the so-called

prediction horizon, that is, N time steps into the future.

In principal, the search for f in (1) is over the set of all possible

functions, but in practice f is often restricted to families, such

as Volterra functions or neural networks [9]. Identification of

the lag sets (i.e. the best combination of values of n and m) is

typically performed iteratively in a manner highly dependent on

the expertise of a control engineer.

Neural networks (NNs) have been widely used for nonlinear

dynamic system identification. In order to enhance the accuracy

while minimising the model size, an architectural refinement

stage is often required. For instance, NeuroEvolution of Augmenting

Topologies (NEAT) [10] uses a genetic algorithm (GA)

to evolve both model structure and the associated parameters of

neural network models.

A further consideration with Volterra approximators and, especially,

neural networks is the large number of parameters that

have to be estimated during training, which implies a requirement

for a large amount of training data. Moreover, with reference

to (1), while training NNs can approximate the function f ,

determining the lag sets specified by n and m usually requires the

embedding of the NN training within some global search for the

network inputs determined by n,m, the so-called feature selection

problem, i.e. a search problem embedded within another search

problem.

To address the challenge specified by (1), an increasing number

of researchers have applied genetic programming (GP) to

nonlinear dynamic systems identification problems [11,12] due to

the advantage of being able to automatically optimise both model

structure and its parameters simultaneously during evolution.

Basic GP, however, has often been used to evolve the function

f either as a simple regression problem (i.e. without the autoregressive

terms yk, yk−1, . . . , yk−m), or using pre-defined lags sets,

that is, pre-specification of n and m in (1).

Rodríguez-Vázquez and Fleming [13] used GP to identify a

number of dynamical systems. Grosman and Lewin [11] used GP

to generate an empirical dynamic model of a process, a mixing

tank, and then applied it in a nonlinear model predictive control

(NMPC) strategy. The results show that the GP method provided

significantly better regulatory and servo performance than more

traditional control approaches. Recently, Feng et al. [12] also

investigated the performance of GP on non-linear dynamical systems

and NMPC, and claimed that a GP based predictive controller

can obtain satisfactory performance.

In the model training stage, however, Rodríguez-Vázquez and

Fleming, Grosman and Lewin [11], and Feng et al. [12] employed

user-specified, pre-determined lag sets, which are normally very

time-consuming to determine manually in practical applications.

Hinchliffe and Willis [14] also used GP to evolve discrete-time

models of dynamic processes, however, evolution of the appropriate

lag set of input variables was included by adding unary

back-shift (i.e. time lag) operators to the GP’s function set. The

experimental results suggest that the performance of GP shows

little difference with filter-based neural networks in terms of

model accuracy on an extruder case study. The significant point in

Hinchliffe and Willis’ [14] work is that their GP formulation is not

only able to approximate model structure (f ), but also construct

appropriate lag sets and not require their pre-specification.

Taking advantage of the fact that the Hinchliffe and Willis

GP scheme is able to evolve both model structure and lag sets

automatically during the evolution process, in this paper, we

describe the use of genetic programming for creating the dynamic

model necessary for buildings MPC. We believe this to be the first

report of the demonstration of buildings MPC using learned GP

models. As is common in the control field, we have considered

a system simulation in order to rapidly and comprehensively

explore the issues involved.

To further underscore the advance made in this paper, it

is worth briefly reviewing the process currently used for constructing

a grey-box predictive models of buildings. Following

the much-cited paper by Hazyuk et al. [6], typically analogous

resistor–capacitor (RC) linear networks comprising various numbers

of R’s and C’s, each network representing the different physical

elements (walls, floors, rooves, etc.), are manually assembled

from expert knowledge of the building. This overall composite

RC network is combined with injected heat gains from the heating

system, solar radiation through windows, etc. (modelled as

voltage or current sources) to produce an overall state–space

model. It is important to note that the heating and solar inputs are

non-linear functions of their controllable variables. For example,

energy transfer from a hydronic radiator is a non-linear function

of the mean water temperature in the radiator — see [6] for

details. Having hand-assembled a model structure, it is necessary

to identify the model’s parameter values, a task which is generally

regarded as ‘‘difficult’’ [6, p. 385], and requires input/output response

data from the building; this process is typically performed

using non-linear least-squares fitting. Unfortunately, parameter

identification is sometimes problematic due to unidentifiability —

the inability to sufficiently accurately determine a parameter’s

value due to numerical deficiencies of the model [15]. Overcoming

unidentifiability requires judicious modifications to the

model followed by re-estimation until the conditions for identifiability

are met. At that point, the calibrated model can be

validated against data from the building independent of that used

for parameter calibration; if the predictive ability of the model

is insufficient, the whole process is iterated until a satisfactory

2

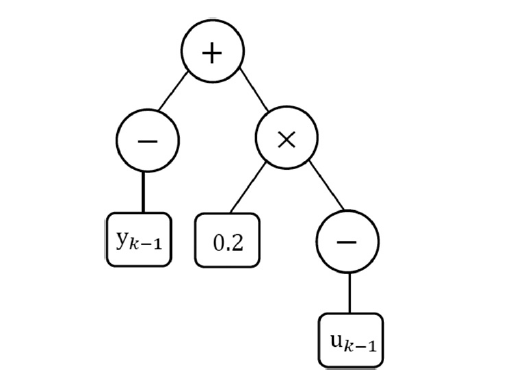


Fig. 1. Simple example GP tree.

model structure is found. The amount of highly-skilled human

intervention at every stage of this process directly motivates the

automation of the construction of predictive models to render

MPC economically-viable for buildings. A credible route to this

automation is the principal contribution of the present paper.

In Section 2, we describe genetic programming for modelling

dynamical systems and give an example for a benchmark problem

from the chemical engineering literature. We describe the building

control methodology we have used in Section 3 together with

the procedures necessary for successfully identifying a predictive

GP model of the test building. In Section 4 we report typical

results of the performance of the predictive GP model as well

as the performance of the model predictive control scheme. In

this paper, we present only representative, typical results and

defer detailed discussion of parameter settings, etc. to a future

publication. We do, however, consider these issues together with

future work in Section 5. We conclude the paper with Section 6.

2. Genetic programming

Inspired by biological evolution processes, evolutionary algorithms

(EA) solve problems by applying the theory of natural

selection to a population of individuals with the expectation of

evolving fitter models. Genetic algorithms (GA) are one class

of EA. Basically, a GA consists of a reproductive strategy for

generating offspring with better fitness using the principal genetic

operators of crossover and mutation. GP is a subset or

an extension of GA. The essential principles of GA and GP are

similar although solutions in GP are expressed as programmes

with hierarchical tree structures, which consist of pre-specified

functional and terminal nodes. This flexible tree structure provides

a dynamic and variable representation. A typical example

of such a GP tree is shown in Fig. 1, and its functional expression

is given in (2).

y(k) = (−yk−1) + (0.2 ∗ (−uk−1)) (2)

Generally, evolutionary algorithms can be classified into two

different types: steady-state and generational. In steady-state

evolution, one (or two) offspring are produced at each step and

appended to the population; the population size is then reduced

down to its original size by removing the weakest one (or two)

individuals. (In fact, the term ‘steady-state’ is a misnomer —

quasi-steady state would be more accurate.) In generational algorithms,

on the other hand, a whole new child population is

produced by repeated selection from a parent population before

the child population is swapped to become the parent population

and the process repeated. In this paper, steady-state GP is

used since this appears to yield superior search results [16]. The

following algorithm describes the evolution process of a typical

steady-state GP.

• Step 1: Population initialisation

In GP, candidates in the initial population are randomly

generated. The process of creating random trees can be implemented

in different ways [17], but two simple methods

(the ‘full’ and ‘grow’ strategies [17]) are extensively used.

In the ‘full’ method, the initial trees are created up to a

pre-defined maximum depth; the depth of a GP tree is the

minimum number of edges that need to be traversed to

reach the deepest leaf starting from the tree’s root node.

Trees are generated by randomly selecting nodes from the

function set until all the leaves reach the maximum tree

depth. In the ‘grow’ method, trees are created with more

diverse structures with some probability of terminating tree

growth before reaching the depth limit.

In order to initialise the population of trees with a variety

of shapes and sizes, Koza [18] proposed a ramped half-andhalf

method where half the initial population is created

using the ‘full’ method and half using the ‘grow’ method. In

the present work, we have used this ramped half-and-half

method for population initialisation.

• Step 2: Fitness evaluation

The performance of each tree is evaluated with a fitness

function, which is used for estimating how well a solution

performs on the given problem. Then the population

is sorted according to fitness value. Solutions with higher

ranks are more likely to be selected as parent trees to breed

child candidates in the evolution process.

• Step 3: Offspring generation

At each iteration, two GP trees are selected as parents.

Two main genetic operations, crossover and mutation, are

then applied to produce new offspring solutions. Specifically,

the crossover operator randomly selects a crossover

point in each parent tree. The child trees are then generated

by crossing over and splicing together the two trees at

the selected crossover points between two parent trees, as

illustrated in Fig. 2.

The mutation operation modifies a GP tree by randomly selecting

a mutation point in a tree, and then replacing it with

a new, randomly-generated subtree, as illustrated in Fig. 3.

After crossover and mutation, the fitness values of the newly

generated offspring are evaluated. The population is then reranked

after the appending the offspring solutions and the

two least-fit individuals deleted to return the population to

its original size.

• Step 4: Process termination

The above procedures are iterated from step 2 to step 3 until

user-specified termination conditions are met; here we have

used a fixed number of iterations.

One of the fundamental problems of GP is bloat — the inexorable

growth in tree size with no accompanying improvement

in fitness. The use of multiobjective optimisation in GP, however,

can reduce the effects of bloat by providing a selective pressure

that favours smaller models — so-called parsimony pressure. In

order to generate compact and accurate models, we have used

the twin fitness measures of tree size (number of tree nodes)

and mean squared error (MSE) over the dataset as two noncommensurable

objectives. The Pareto dominance based ranking

scheme [19] was used to rank the individuals in the population.

A fitness vector a = (a1, . . . , ap) is said to dominate b =

(b1, . . . , bp) if and only if a is partially less than b, i.e., a ≺ b

∀i : ai ≤ bi ∧ ∃i ∈ 1, . . . , p : ai < bi; in our case the fitness

vectors are the 2-vectors with node count and MSE as elements.

During the evolution process, trees with higher ranks have bigger

probabilities of being selected as parent trees to produce child

candidates, and at the end of the run the population comprises

3

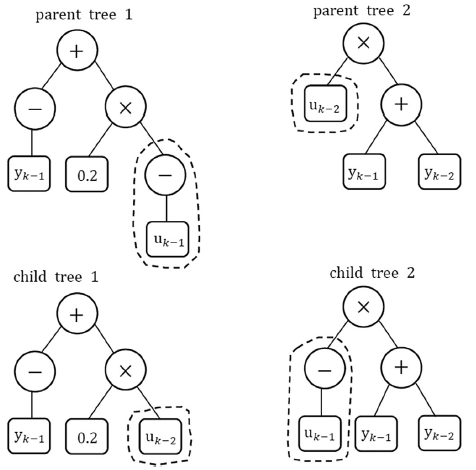


Fig. 2. Example of subtree crossover.

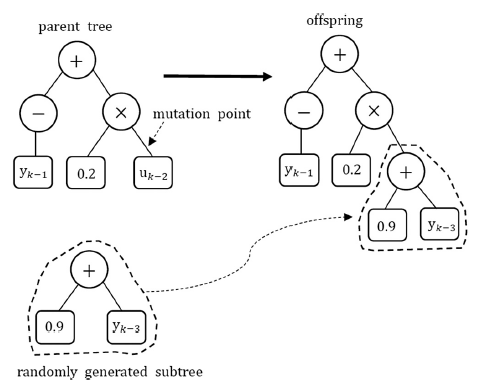


Fig. 3. Example of subtree mutation.

a set of individuals which trades-off compactness against goodness

of fit (small MSE) to the training data. Typically, this final

population spans the spectrum of small individuals with large

MSE values (underfitted models) through to large models with

small MSE values (overfitted models). We select a single, final

model as the one which has the smallest MSE over a validation

set independent to the training set.

The performance of GP on nonlinear dynamic system identification

was first evaluated on a benchmark chemical engineering

process, the Eaton–Rawlings reactor model in the following section.

Having demonstrated satisfactory performance on this task,

GP was applied to finding a dynamical model of the test building

for MPC.

2.1. Identification of the Eaton-Rawlings reactor

There have been many reports in recent years exploiting the

potential of GP for system identification, particularly in chemical

engineering applications [20]. In order to assess the suitability

of GP for nonlinear dynamic system identification, one-step-head

(OSA) prediction of a well-known benchmark chemical process,

the Eaton–Rawlings reactor model, was investigated. The Eaton–

Rawlings model [21] describes a second-order reaction occurring

in an isothermal continuous stirred-tank reactor (CSTR). The dynamics

of this reactor are expressed by the first-order, nonlinear

ordinary differential equation

dy

dt

= −hy2 −

yu

V

+

du

V

(3)

where y is the concentration in the CSTR, h is the kinetic rate

constant for the reaction, V is the reactor volume, and d is the

inlet concentration of the reactant. The manipulated variable u is

the inlet flow rate.

If the manipulated input u is assumed to change only at regular

sampling instants tk, an exact discretisation is easily derived

from the continuous-time equation; see [21] for full details.

y(k) =

[1 − τ (k − 1)μ(k − 1)]y(k − 1) + 2dτ (k − 1)μ(k − 1)

1 + τ (k − 1)[y(k − 1) + μ(k − 1)]

(4)

where

τ (k − 1) =

tanh [hT

√

μ2(k − 1) + 2dμ(k − 1)] √

μ2(k − 1) + 2dμ(k − 1)

(5)

μ(k − 1) =

u(k − 1)

2hV

(6)

In this experiment, h was 1.50 litre/mole-hr, V was 10.51 litre,

d was 3.5 mole/litre [21]. The inputs uk were a sequence of steps

of uniformly-distributed random amplitudes ranging from 0.5 to

5.0 litres per hour with a switching probability of 1.0. This input

sequence was used to perturb the reactor model (4).

To facilitate direct comparison with previous, conventional

modelling approaches, we have followed the procedure in Pearson

[21] and generated 100 statistically-independent training

sequences, each of length P = 200. The reactor responses to these

input sequences were calculated according to the discretisation

formula (4).

The performance of a GP solution was ranked by two objectives:

tree size and the MSE. The parameter settings for the

GP evolution are described in Table 1; for the identification of

the Eaton–Rawlings model, we used GP constants in the range

[0.0 . . . 1.0].

In each GP experiment, a set of solutions was obtained after

training from which the candidate with the smallest MSE over a

validation dataset was finally selected as the best model for this

run. Thus, after 100 independent training processes, the best GP

model with the smallest validation MSE among the selected 100

trees was picked as the best overall solution. The best GP model

selected had a validation MSE of 0.000121458.

We made quantitative comparison with the model – a nonlinear

autoregressive moving average model with exogenous inputs

(NARMAX) – that exhibited the best performance compared to

other hand-tuned model structures and lags studied by Pearson

[21]; the same training datasets were used to train the

NARMAX models by minimising the mean squared error metric

(8) using the NLopt nonlinear optimisation library.2 The best

NARMAX model [21] is given by:

y(k) = y0 + α y(k − 1) + β u(k − 1) + γ u(k − 1) y(k − 1) (7)

2 https://nlopt.readthedocs.io/en/latest/.

4

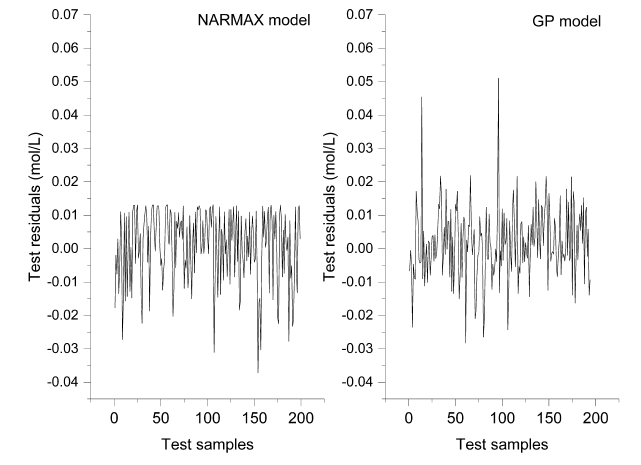
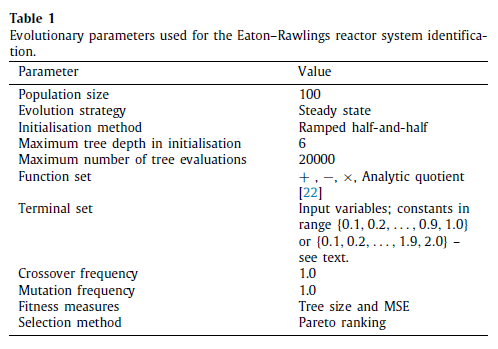


Fig. 4. Test residual comparison between the NARMAX model and the best GP model.



where y0, α, β, and γ are unknown parameters to be determined

by minimising the objective function, and Q is the length of the

training sequence:

J(y0, α, β, γ ) =

ΣQ−1

k=1

[ˆy(k + 1) − y(k + 1)]2 (8)

where ˆy(k + 1) is the one step ahead predicted value at time k,

and the y(k + 1) is the measured value at time k + 1.

The best validation MSE of the NARMAX models was

0.000120801, nearly equal to the value of obtained from the best

GP tree. The residuals – the differences between the true and

predicted values – of the best NARMAX and GP models over the

corresponding validation sets are shown in Fig. 4 from which it

can be seen that the GP tree exhibits comparable model accuracy

to the best NARMAX model. The residuals of the NARMAX model

show a number of negative spikes lower than −0.02, with the

absolute value of the biggest residual around 0.04. The GP model

shows two significant positive spikes, but with most of the

residuals lying in a small range around zero.

The encouraging approximation ability of the GP model on the

benchmark Eaton–Rawlings problem suggests that GP is suitable

for more general nonlinear dynamic system identification problems.

Particularly, GP does not require the functional form of the

model to be pre-specified — rather, this evolves during training.

This advantage makes GP a potential technique for identifying a

wide range of real world, nonlinear dynamic systems for which

the underlying physical principles are not known.

3. Building control methodology

In this section, we describe the procedures employed for the

MPC of buildings using predictive models obtained through a

GP-based system identification. Fig. 5 depicts the components of

the simulation system used in this work. We used an industrygrade

simulator for building physics, described in Section 3.1,

to simulate the responses of a test building. This simulator provides

a standardised interface – the Functional Mockup Interface

(FMI) [23] – that allows the interconnection of external software

units — see Section 3.1. We used this facility for two separate

tasks: first, for the open-loop collection of system identification

(SID) data detailed in Section 3.3, and second for the simulation

of the building under model-predictive control, as explained in

Section 3.6. In Section 3.5, we describe how we employed GP

using the collected SID data to obtain the required predictive

models for MPC.

3.1. Building simulator – EnergyPlus

EnergyPlus is a building energy simulator used to model

energy consumption based on dynamic heat transfer calculations

[24]. The description of the building is provided to EnergyPlus

as a text file – the input data file (IDF) – that follows a

prescribed format. The file controls all aspects of the simulation

from the building geometry and fabric to the building services

and other simulation parameters, such as occupancy.

The (key) influence of the external weather is incorporated

into the building simulation using a separate file containing

weather data, a so-called weather file. This allows repeating the

computations under different climatic conditions. In this work,

we have used design weather files generated from UK meteorological

data collected at a station located in Manchester, UK. Two

5

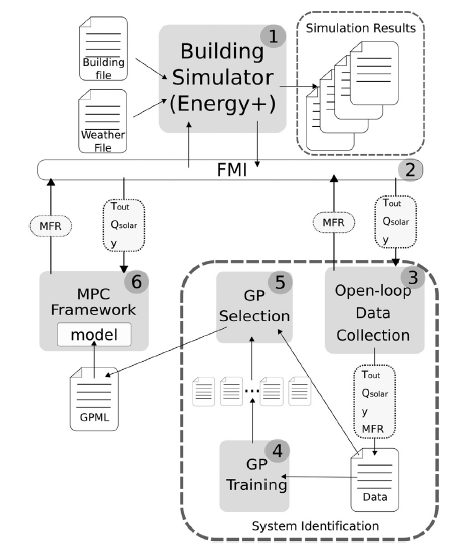


Fig. 5. Overview of the process employed in this work for MPC. The mass

flow rate (MFR) of hot water through the radiator, external temperature Tout ,

the sum of direct and diffuse solar radiation Qsolar and zone temperature y

are communicated to/from the EnergyPlus simulator via functional mock-up

interfaces (FMIs).

different weather files, both containing one year’s data, were used

in this work: the training and validation datasets were extracted

from the first weather file, while the second file was used to test

the model for a whole unbroken year.

EnergyPlus supports Functional Mock-up Interfaces (FMIs)

[23], a standardised interface for coupling software units for

co-simulation. These software units can add a variety of functionalities

to the simulation and are referred to as ‘slaves’. The

main simulator – EnergyPlus in our case – is referred to as the

‘master’. In practice, the FMI defines a set of C language function

prototypes that need to be implemented by the slave unit. The

master will then call these functions at appropriate times during

the simulation to perform various operations, such as send data,

perform calculations, read data, etc. Here we make two distinct

uses of the FMI functionality (see Fig. 5): first, we inject an

excitation sequence to perform open-loop system identification

(described in Section 3.3). Referring to Fig. 5, the mass flow rate

(MFR) to the heating radiator is varied, and the external temperature

(Tout ), sum of the direct and diffuse solar radiation (Qsolar )

and zone temperature (y) are logged at every time sampling

interval. Second, having trained the GP models on the system

identification data collected in the previous step, we used FMIs

to control the building’s heating during model predictive control

experiments (described in Section 3.6). Again referring to Fig. 5,

here under MPC control, the current environmental conditions

(Tout , Qsolar and y) are acquired from the EnergyPlus simulation via

FMIs, the optimal MFR control value calculated externally taking

into account the heating schedule, and this optimal MFR applied

at the next time step update.

3.2. Test building description

For this initial report of implementing MPC using a learned

dynamic model, we developed a single zone space with a conventional

hydronic radiator supplied by a boiler producing water

at a fixed output temperature of 67 ◦C. The heating system was

sized using EnergyPlus which determined the maximum flow of

hot water through the radiator to be 0.11 kg/s. The simulated test

building is illustrated in Fig. 6. The zone is a square room with

dimensions of 10 m × 10 m and a height of 3 m. All four walls

contain one double glazed window unit measuring 2 m × 2 m

with a sill height of 0.5 m, and placed at the centre of the external

walls. This design has a window-to-wall ratio of 13% with equal

exposure to North, East, South and West directions. The single

zone space has been set to be located in Manchester, UK, which

has an oceanic climate (Köppen classification = Cfb) and classified

as ASHRAE (American Society of Heating, Refrigeration and Air

Conditioning Engineers) climate zone 5c. The construction sets

and internal gains for this climate recommended by ASHRAE

Standard 189.1 [25] were considered for this space to make sure

a realistic set of inputs was defined in the building model for

estimating the internally-generated heat as well as the heat loss

from the façades.

We have used a setpoint temperature of 20 ◦C during occupied

(working) hours of 9am to 5pm. Outside those hours, the schedule

specified that the zone temperature was ≥ 6 ◦C to ensure frost

protection. For the present set up, we have used this schedule

for seven days a week to gather as much data about the MPC

operation as possible.

The airflow through the space consists of infiltration (0.00023

m3/s per m2 of exterior surface) and a ventilation rate of 10 l/s

per person in accordance with the Chartered Institute of Building

Services Engineers (CIBSE) Guide A [26]. The occupancy density

was 0.0565 persons/m2, the default value for office buildings

in EnergyPlus based on the ASHRAE 189.1 2009 standard. Heat

gains from people, lighting and electrical equipment were also

incorporated in a schedule.

3.3. Open-loop system identification

The design of appropriate excitation signals for collecting

identification data is the most crucial step in system identification

as the gathered data are required to be informative enough

to capture the underlying system dynamics under all relevant

operating conditions while for practical reasons, the duration of

the SID experiments should be as short as possible to minimise

disruption. Mathematically, the amplitude of the excitation signal

should cover the full range so as to maximise the power of the

excitation signal and thus the signal-to-noise ratio; the spectrum

of the input signal should excite all frequencies of interest.

For linear systems, pseudo-random binary sequences (PRBSs)

[27] are commonly used for system identification. In a PRBS, the

signal switches between two fixed amplitudes in such a way that

the autocorrelation function of the sequence approximates the

properties of white noise, and hence excites all modes of the

system. For nonlinear systems – such as that under consideration

here – switching between two fixed amplitudes cannot capture

the nonlinear behaviour [9], and so we have employed amplitude

modulated pseudo random binary sequences (APRBSs) [9] in which

the amplitude of a conventional PRBS is randomly varied, thereby

probing the nonlinear characteristics of the system.

A PRBS sequence was generated using linear feedback shift

registers where the length of the excitation sequence is controlled

by a characteristic polynomial of some degree n, and where each

polynomial coefficient was either 0 or 1. The maximum repetition

period is given by (n2 − 1) (i.e. the maximum length of the

6

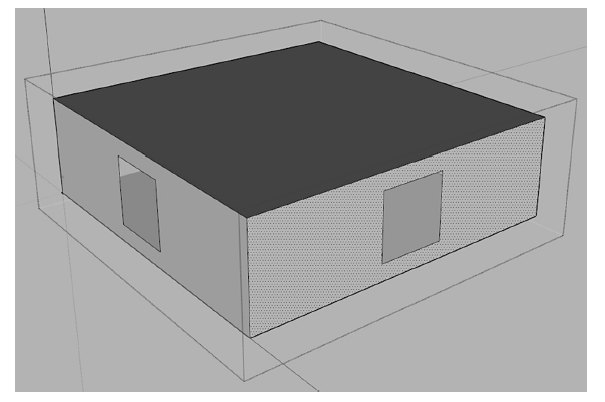


Fig. 6. SketchUp representation of the simulated building.

sequence before it starts to repeat itself). The consecutive occurrence

of the same bit is referred to as a plateau. We employed the

polynomial x7 +x6 +1, resulting in a sequence length of 127 bits

with 64 plateaux, depicted in Fig. 7(a). The interval between the

minimum and maximum radiator flows (0.00 to 0.11 kg/s) was

divided by the number of plateaux in the PRBS resulting in a set of

different amplitude levels, which were randomly assigned to the

PRBS’s plateaux, thereby generating the APRBS [9]; an example

sequence is shown in Fig. 7(b). The process of randomly assigning

amplitude levels to the PRBS plateaux was repeated to obtain a

set of different excitation sequences. Note that each repetition

of the process is likely to generate a completely different APRBS

cycle, as seen in Figs. 7(b–c).

In addition to the characteristic polynomial and the interval

of the input sequence, an APRBS is specified by a minimum holdtime

Th, that is the duration of each bit; Nelles [9] suggests that

the minimum hold-time should be the same as the dominant time

constant of the process. In our case, the only input that can be

excited is the mass flow rate through the radiator so we estimated

the dominant time constant as approximately 30 min by applying

a step excitation to the simulated zone. As a consequence, a single

APRBS-7 cycle takes around 3,810 minutes (about 2.6 days), as

depicted in Fig. 7.

3.4. Input selection

In system identification, the selection of model inputs is key to

model accuracy. Too many redundant or irrelevant input variables

hampers the search while increasing the computational burden.

Conversely, if input variables of significant influence are omitted,

the model will have systematic errors and be more likely have

poor prediction accuracy. The input and output variables used in

this paper are listed in Table 2. Full details of the input selection

criteria and experiments will be published elsewhere, but, in

brief, we performed a sensitivity analysis over the set of weather

variables with respect to predictive accuracy leaving us with Tout

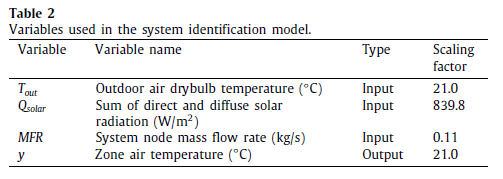
and Qsolar as the most influential; the mass flow rate (MFR) is,

of course, the manipulated variable and y the predicted zone

temperature. All the variables were scaled so as to have the

training values falling in the range 0 to 1. The scaling factors used

are listed in Table 2.



3.5. Genetic programming for building identification

• Training & validation

A dynamical predictive GP model was developed based on

an EnergyPlus simulation model and the open-loop excitation

data (see Section 3.3). Two different weather files

were employed: One weather file, denoted TRY, comprising

365 days and 35,040 samples, was used to generate

data for model training and validation (model selection).

The other dataset, denoted DSY and of the same size, was

used for estimating the model generalisation and prediction

accuracy. A particular challenge with this MPC application

is that weather conditions play a very important role in

determining the internal temperatures of the building but

they cannot be experimentally perturbed in the same way as

the radiator MFR variable. We have thus used two weather

files to allow an evaluation of performance over a complete

year independent of the training/validation data.

Since the (approximate) time constant of the simulated

building is ∼30 min, the sampling interval for the MPC was

set at half this figure, namely 15 min. The selected input

variables (see Section 3.4) were sampled every 15 min for

training, validation and testing of the GP models and the

MPC process predicts temperatures on this interval.

Given a GP model f , at time k the prediction of the zone

temperature ˆy(k+i) at time (k + i) is approximated from:

ˆy(k+i) = f (uk+i−1,uk+i−2, . . . , uk, uk−1, . . . ,

ˆy(k+i−1), ˆy(k+i−2), . . . , yk, yk−1, . . .) (9)

where i ranges from 1 to N, the length of the prediction

horizon, and u are the indexed sequence of exogenous input

vectors. In this experiment, a u vector consisted of

7

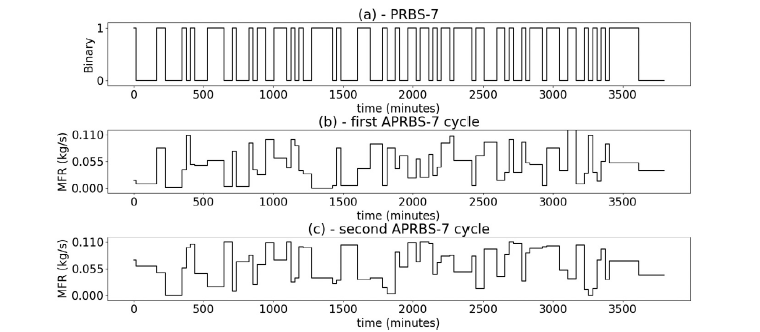


Fig. 7. A PRBS-7 sequence (a) and two different examples of APRBS-7 cycles (b–c) generated over a minimum-to-maximum flow amplitude range of 0.0 to 0.11 kg/s.

three variables: Tout , Qsolar , and MFR – see Table 2. The zone

temperature y is the predicted variable.

In the training phase, all the input and output information

is known since u consists of measured values determined

by the APRBS excitation sequence (Section 3.3) and the

known weather data; the zone temperatures up to and

including the current time k are also known. For multistep

ahead prediction, the required autoregressive values

later than time k use previously predicted values from a

series of one-step ahead predictions. For example, at time

k, ˆy(k+1) = f (. . . , yk, yk−1, . . . , yk−m). To predict two steps

ahead, ˆy(k+2) = f (. . . , ˆy(k+1), yk, yk−1, . . .). Note the use of

a predicted zone temperature ˆy(k+1) at time (k + 2) since

when the model is used in its ultimate control application,

the actual value y(k+1) will be unknown as it lies in the future

– it therefore has to be estimated. Similarly, the prediction

three steps ahead ˆy(k+2) uses both ˆy(k+1) and ˆy(k+2), and so

on. Previously predicted values are used ∀i ∈ [1 . . . N], as

necessary.

Two objectives are used to measure the performance of candidate

models during evolution: tree size and MSE. The tree

size indicates the complexity of a GP model, and provides

parsimony selection pressure that favours simpler models

during the evolutionary process. We also seek to minimise

the MSE over the training dataset by:

MSE =

ΣPk

=k′

ΣN i=1[ˆy(k+i) − y(k+i)]2

[P − max(n,m)] × N

(10)

where N is the length of the prediction horizon, and P is

the largest index on the training dataset used. Since we

require the GP model to provide accurate predictions over

the whole prediction horizon, minimising (10) provides a

selective evolutionary pressure to achieve this. The values

of upper limit on the outer summation and the normalising

term in (10) requires some clarification: Suppose we have

Q records of available training data. To train a model that

predicts N steps ahead, the final N records of the dataset can

only be used for evaluating (10) – the index k cannot exceed

(Q−N). Similarly, for an autoregressive model with n lagged

u values and m lagged y values, the first max(n,m) records

of the training set are needed to calculate the very first

prediction. Consequently, k′ , the lower limit on the outer

summation in (10), cannot be less that [max(n,m) + 1]. In

summary, the MSE in (10) is calculated over (Q − N) −

[max(n,m) − 1] consecutive records. (Conventionally, the

lower limit of this outer summation is taken as k = 1 and

any lagged inputs with (strictly) negative k indices are taken

as zero. We have not used this approach here as, in our

experience, this sometimes produces anomalous transient

predictions.)

The detailed GP parameter settings for building identification

were identical to those shown in Table 1, except we

have used constants in the range [0.0 . . . 2.0].

• Exporting the Selected GP Tree

After model validation, the best GP model was selected

for use in the EnergyPlus MPC framework. Rather than the

cumbersome inconvenience of embedding the GP training

within the MPC framework, we have exported the trained

GP model using the Genetic Programming Markup Language

(GPML) [28]. GPML is an XML-based standard for the interchange

of genetic programming trees. The implementations

of reading and writing GPML are simple and straightforward

since a number of mature, open source XML libraries

are available. A trained-and-validated GP tree can thus be

directly embedded as a ‘plug-in’ component using GPML

in larger systems, which provides both convenience and

modularity.

3.6. MPC test framework

Based on the model f in (1) approximated with a GP as

described in Sections 3.3–3.5, a control law could, in principle,

be obtained as the inverse of f – that is a mapping from desired

states to the necessary inputs. However, as f is dynamic and nonlinear,

calculating its inverse is not a trivial task. The alternative is

to perform an explicit optimisation at the current time k of the set

of values Uk = {uk, u(k+1), . . . , u(k+N−1)} using f , where N is the

prediction horizon, and adjusting Uk to yield the desired sequence

of setpoint temperatures. Thus we obtain Uk from:

Uk = argmin

ΣN

i=1

J(k + i) (11)

where N is the length of the prediction horizon. Since the (approximate)

time constant of the building’s response was determined

to be 30 min, and the MPC sampling interval was 15 min,

we adopted a value of N = 12 giving a prediction horizon of 3 h.

The function J is defined as:

J(k + i) = (ΔTk+i)2

  

temperature

+λ0 |ΔUk+i|   

control effort

+λ1uk+i

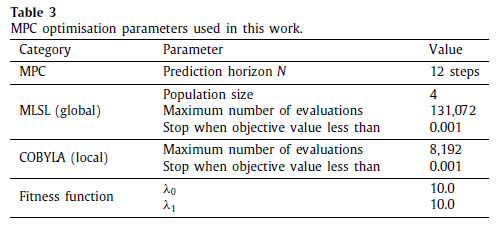
energy

(12)

where ΔTk+i = ˆy(k+i) − r(k+i) is the difference between the

predicted ˆy(k+i) and setpoint (i.e. desired) r(k+i) temperatures at

8



time k + i, and ΔUk+i = uk+i − uk+i−1 is the control effort. The

first term in (12) obviously penalises deviation from the desired

setpoint temperature, while the second term seeks to minimise

the extent of changes in the control variable; such a term is

frequently included in an MPC setup to minimise wear on the

system’s actuators.

The third term in (12) seeks to minimise the sum of the input

quantity, which in the present case is a proxy for input energy.

We found it necessary to include this term in (12) to ensure

that heating was turned off outside working hours when the

constraint on the setpoint temperature was relaxed to simply

being >6 ◦C to ensure frost protection. Unless this explicit energy

minimisation term was included, (11) could be minimised by

maintaining the zone temperature at 20 ◦C – obviously, >6 ◦C

– but setting the sum of the magnitudes of the control efforts

(|ΔU|) to zero. That is, not turning off heating at the end of the

working day thereby undesirably maintaining heating during the

night.

Note that the second and third terms in (12) are weighted

by the regularisation constants λ0 and λ1, which place differing

relative penalties on each of the three factors in (12). The values

of λ0 and λ1 were determined by grid search with the aim of maximising

their values subject to acceptable temperature regulation.

Predictions of zone temperature ˆy(k+i) are calculated using the GP

model described in Section 3.5.

One notable point is that in the training process, the weather

variables Tout and Qsolar are always assumed known, and for which

we have used measured values. During the validation and test

phases, however, the practical use of the model means that future

values of Tout and Qsolar are unknown. Consequently, we have

used persistent predictions for future (as yet unknown) weather

variables. Namely, the value of the weather variable at time k

is assumed to persist unchanged for the whole of the current

prediction horizon. Persistent weather prediction is known to be

reasonably accurate over the short-term [29,30] while having the

advantage of being simple to implement.

The minimisation in (11) was performed using an implementation

of the nonlinear, derivative-free optimiser COBYLA [31] together

with the Multi-Level Single-Linkage (MLSL) procedure [32,

33] from the NLopt nonlinear optimisation library.3 Although

MPC has the advantage of being able to straightforwardly incorporate

constraints on the solution, in the present work we have

used no such constraints.

The detailed MPC optimisation parameter settings for building

testing are shown in Table 3.

4. Results

In Section 4.1 we describe the results of training the GP predictive

model using the open-loop system identification data

produced using the procedure set-out in Section 3.3. Section 4.2

3 https://nlopt.readthedocs.io/en/latest/.

presents the control results from using the trained GP predictive

models in an MPC controller to regulate the zone temperature of

the building model described in Section 3.2.

4.1. GP model training

We conducted thirty GP training runs, each with an independent

initial population, using the open-loop system identification

data generated with the procedures described in Section 3.3 to

obtain 30 individual models with the best validation set MSE

per run. Among these, the model with the smallest validation

MSE overall was finally selected as the best model. January’s data

(2,880 records) were used as the training dataset and February’s

data as validation dataset. Typically, the CPU runtime of each

independent experiment takes ∼400 s (on a given computer with

3.30 GHz CPU).

The residuals (i.e. errors) for each of the i-step ahead predictions

(i ∈ [1 . . . N]) measured over the 12-month independent

test set for the best GP model are shown in Fig. 8. Here we

are assessing the important performance measure of whether

the model produces sufficiently accurate predictions over the

whole (test) year, and does not, for example, erroneously demand

heating of the building in the middle of summer.

From Fig. 8, residuals of the one step ahead prediction fall into

range from −1.25 to 1.75 ◦C; even in the summer months (June

to August) , most residuals are below 1.5 ◦C. Unsurprisingly, as

the predictions extend further into the future, the envelope of

residuals expands although only slightly. In addition, a distinct

seasonal ‘bow’ becomes more noticeable with increasing i value.

Our choice of the metric in (10) was deliberately designed to

give equal weight to the prediction errors over the whole prediction

horizon. In 12-step-ahead prediction, residuals in January,

February, March, November and December range from −2 to

2.5 ◦C. Residuals in the months such as May, June, July and August

reach their highest values of 4 ◦C and with an average lower

bound of 0 ◦C error. After increasing during summer, the sizes of

the residuals decrease later in the year. In summary, the GP model

provides promising predicted temperatures: the magnitudes of

the residuals expand with increasing prediction step size i with

the biggest residual less than 4 ◦C. The best model presented in

GPML form can be found at:

https://figshare.com/articles/gpTreeConstantWFInVall\_xml/73

98797

4.2. MPC performance

Fig. 9 shows a typical result of controlling the test building

during the month of February (from the 32nd to 59th day of

the test year) using the MPC framework from Section 3. The test

weather data are independent of the data used to train/validate

the predictive model. The reference value r(k+i) was set to match

20 ◦C during working hours (9:00 to 17:00). To achieve frost

protection out-of-hours, the reference value was set at ≥ 6 ◦C.

That is, we only apply a temperature penalty out-of-hours if

the temperature falls below the frost-protection reference value.

Formally, ΔT(k+i) out-of-hours is defined as:

ΔT(k+i) =

{

ˆy(k+i) − r(k+i) if ˆy(k+i) < r(k+i).

0 otherwise.

(13)

As described in Section 3.6, we have predicted future (unknown)

weather values using persistence, that is, assuming the

variable has the same value over the whole of the prediction

horizon as it does at the start.

The upper plot in Fig. 9 shows the zone temperatures, and also

a }1 ◦C range during working hours (dotted lines). The lower

9

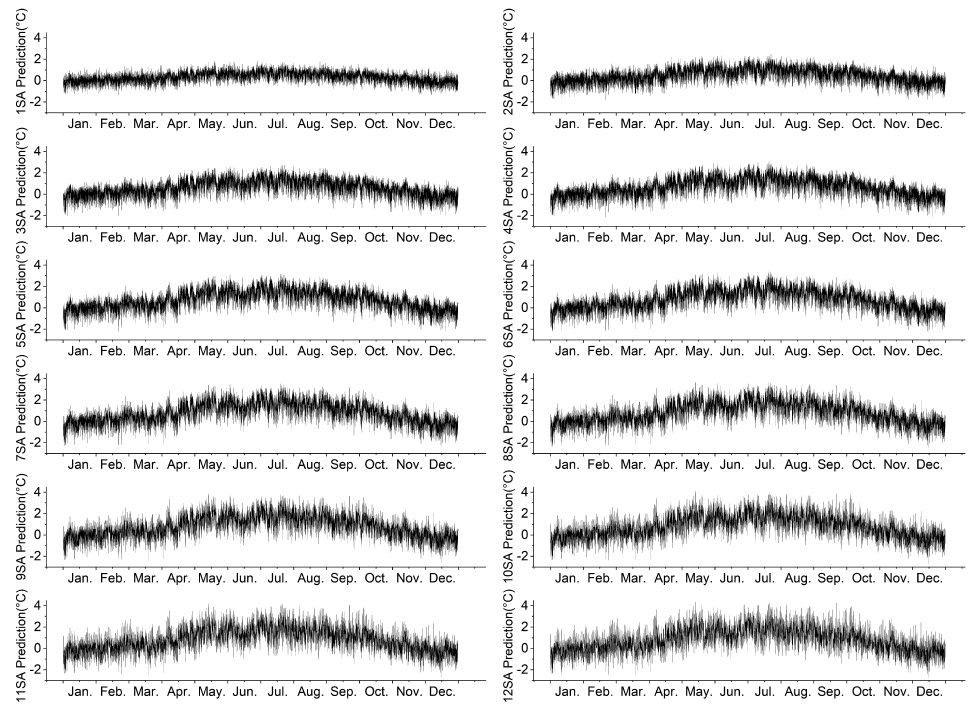


Fig. 8. Residuals (predicted - actual zone temperatures in ◦C) of the selected GP model over the test dataset for different future predictions. Each plot shows the

residuals for a given number of steps ahead — for example, ‘‘OSA’’ = 1-step head, ‘‘2SA’’= 2-steps ahead, etc. The units of the ordinate axes are Celsius.

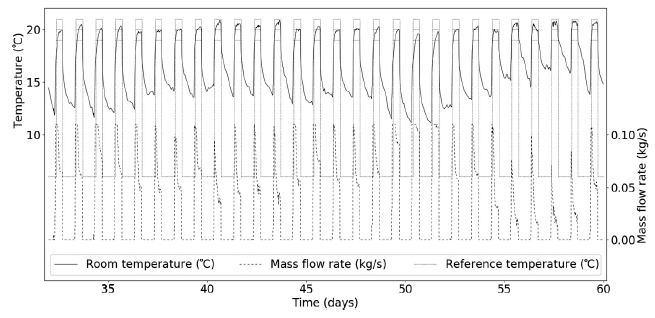


Fig. 9. Typical results of MPC controlling a single-zone room for the (test) month of February. The upper plot is the zone temperature, and the lower plot the mass

flow rate (MFR) controlled variable. The rectangular upper plot represents the temperature schedule. The dotted lines represent the temperature schedule together

with a } 1 ◦C tolerance band shown during occupied hours (9am to 5pm).

plot shows the MFR control variable (hot water flow through the

radiator).

From Fig. 9, it is clear that zone temperatures are mostly

being maintained within the }1 ◦C band during working hours.

A noteworthy feature of the MFR control variable is that it varies

fairly smoothly over the day, and is being reduced to small values

towards the ends of the working days; we infer that MPC is

exploiting the energy stored in the building’s fabric to maintain

the setpoint temperature up to the end of the working day,

thereby avoiding direct heating, if possible, which may lead to

energy savings.

Considering the thermal performance of MPC, it successfully

maintained the zone temperature within the }1 ◦C range for

83.3% and }2 ◦C for 95.2% of the (working) time. The 1 ◦C band

10

T. Dou, Y. Kaszubowski Lopes, P. Rockett et al. Applied Soft Computing Journal 97 (2020) 106695

is generally deemed comfortable, with a small proportion (less

than a quarter) of occupants feeling mildly uncomfortable at the

extremes of the 2 ◦C band [26]. Although there will be some

discomfort for the short periods outside these bands that fall at

either end of the working day, these are rare.

5. Discussion and future work

As stated above, scope of this paper is to present what we

believe to be the first report of buildings MPC using a predictive

model learned data acquired from the building. Our aim here

has been to present and document the methodology we have

used although a great deal of work remains to be done both in

terms of ‘fine tuning’ this, and in extending it. One area that

does needs to be explicitly discussed is comparator methods.

Since the GP-controller regulates the zone temperature generally

within a highly satisfactory } 1 ◦C, and exhibits no instances

of overheating and therefore wasted energy, the only reasonable

basis for comparison is the ease/cost of generation of the

predictive model — see [2]. As pointed out in Section 1, we are

aware of no comparable technique with which to make direct

comparison, and in which both the structure of the predictive

model and the composition of the lag sets are simultaneously

identified. In all other applicable techniques of which we are

aware, the search over possible model forms would need to be

embedded within a search over all possible lag sets (feature

selection). The GP approach used here thus represents a robust

and simple automated workflow for practical application of MPC

with few ‘tuning’ parameters; further GP tends to be fairly robust

to its tuning parameters.

We can identify a number of interwoven topics that will be

the subject of future work, and will be published elsewhere.

Although we have reported only one instance of a predictive

model trained on 30 days open-loop excitation data, optimisation

of the training process clearly needs to be explored systematically.

Although the test residuals shown in Fig. 8 are clearly

adequate to produce acceptable control, as evidenced by Fig. 9,

the model residuals exhibit a noticeable seasonal effect — an upward

‘bowing’ in the middle of the plots. In the summer months,

the actual temperatures are systematically somewhat higher than

those predicted by the model, but in the present application

with only heating of the building, this turns out not to make a

great difference since heating is not necessary in the summer

months. For a more complicated building, however, that includes

cooling as well as heating, these seasonal effects may produce

unacceptable conditions although for a combined heating/cooling

system, the SID procedure would obviously also need to include

excitation of both heating and cooling. Consequently, improving

the model quality is therefore clearly an area for future work, and

a number of factors need to be examined.

The duration of the open-loop excitation experiment: Although

we report only data for 30 days of system identification,

it seems possible to train adequate models with shorter data

sequences than this. The trade-off between the length of the SID

experiment and model quality needs to be explored. Naively,

one would expect model quality to improve with longer SID

sequences (= more training data), but extending the system

identification experiment has implications for both the amount of

energy used during SID as well as the practicality of conducting

the experiment.

In terms of practical application, we have established that

acceptable predictive models can be trained on data accumulated

over 30 days. Ideally, this SID timescale needs to be shortened

to be more compatible with current building project schedules,

and to be integrated with existing commissioning/testing regimes

for the heating system. One potential area of future work is to

use a much shorter SID duration and form the predictive model

using consensus prediction over multiple models [34] as has been

widely used in meteorology, econometrics, etc.

For the sake of simplicity, we have assumed persistent weather

predictions. That is, we assume the weather inputs have the

same values over the entirety of the prediction horizon as they

do at the start of the prediction horizon. Persistence is known

to be acceptable in the short term, but it is possible that more

elaborate methods [35] may give improved results, especially

for larger buildings that mandate longer prediction horizons. In

particular, short-term weather predictions are widely available

online and an avenue of future research is to examine the effect of

replacing the assumption of persistence with more sophisticated

predictions.

The length of the prediction horizon has been chosen to be

around six times the characteristic time constant of the building

(although the step response of the building is clearly not a

first-order characteristic). The trade-offs inherent in selecting a

prediction horizon are well-known in the MPC literature [1]: a

longer horizon allows a more relaxed planning timeframe and

tends to avoid overly aggressive control moves, while producing

more uncertain predictions due to the length of time into the

future over which they are being made. Shorter prediction horizons

face the converse issues. Systematic examination of setting

the prediction horizon in the context of buildings is therefore

warranted.

The MPC framework we have reported uses the rather conventional

objective of penalising deviation from a setpoint, in this

case zone temperature, together with an appropriately weighted

term to minimise control effort (a proxy for actuator wear). In

addition, we have included a term designed to minimise energy

consumption over the prediction horizon, this latter term proving

necessary for proper operation out of working hours. Clearly the

regularisation constants (here denoted λ0 and λ1) will have an

influence on the control although quite how significant these will

be also needs to be investigated.

Such a regularisation framework has been commonly used in

previously published reports on buildings MPC [2], and appears to

have been adopted straightforwardly from its widespread use in

chemical engineering and related industrial applications of MPC.

In process engineering, of course, it is frequently important to

maintain some optimal process temperature to maximise product

yield, etc. Maintaining zone temperatures within a small band,

however, is generally unnecessary in buildings. Indeed relaxing

the temperature constraints on a zone can have beneficial energysaving

advantages. More generally, tuning regularisation constants

is known to be problematic and time-consuming, and to

a large extent, a conventional regularisation framework militates

against our overall objective of automating implementation of

MPC in buildings in order to make it economically viable. Consequently,

alternative minimisation objective functions may well be

more appropriate in a building setting. For example, minimising

energy usage (over the prediction horizon) subject to the explicit

optimisation constraints of maintaining zone temperatures

within, say, a }2 ◦C band.

The system identification experiments reported here involve

open-loop excitation of the building. It is well-known that openloop

excitation can drive the system’s states to extremes since

there is no feedback control to prevent this. Apart from potentially

consuming significant amounts of energy, performing

an open-loop system identification experiment on an occupied

building would probably be unacceptable. Indeed, it is highly

likely that the occupants would take atypical actions, such as

opening windows and doors, to make the internal conditions

more acceptable to themselves, thereby undermining the validity

of the system identification data. Rockett and Hathway [2] have

11

T. Dou, Y. Kaszubowski Lopes, P. Rockett et al. Applied Soft Computing Journal 97 (2020) 106695

already suggested closed-loop system identification as a way of

addressing the shortcomings of open-loop identification for periodic

recalibration of the controller: closed-loop identification [36]

maintains the system under control using an initial predictive

model while typically applying small perturbations to the desired

setpoint from which an improved, control-capable model can be

derived. This process of closed-loop re-estimation can, of course

be repeated periodically as-and-when the building’s characteristics

change. Closed-loop recalibration of MPC’s predictive model

is clearly an area for future work where issues such as: the necessary

excitation sequence and the sensitivity of the re-estimation

procedure need to be explored.

The work presented in the paper has demonstrated successful

MPC implementation over a single-zone building. Clearly extension

to multiple-zone buildings is an obvious area of future work,

where the necessary SID procedures will need to accommodate

multiple, interacting thermal zones.

Finally, although the work presented here has been done in

simulation – as is very common in the initial steps of a control

project – the ultimate ‘proof’ of the methodology is to demonstrate

its use on a real building. This too is currently work in

progress.

6. Conclusions

In this paper, we have reported the first use of genetic programming

to obtain predictive models for the model predictive

control (MPC) of internal building temperatures. Currently, the

large-scale adoption of MPC in buildings is rendered uneconomic

by the time and cost involved in the design and tuning of predictive

models by expert control engineers. We have shown that

GP is able to automate this process using an open-loop excitation

experiment. The resulting MPC simulation is able to maintain

the internal temperature of a single-zone test building to within

}1 ◦C of the desired setpoint most of the time; we further infer

that MPC is able to effectively exploit the heat stored in the

building’s fabric towards the end of a working day rather than

applying direct heating. The results in this paper have significant

implications for enabling the wide-scale deployment of MPC in

non-domestic buildings, and for the potential reduction in CO2

emissions by improving the efficiency of building operation.

CRediT authorship contribution statement

Tiantian Dou: Software, Validation, Investigation, Writing -

review & editing. Yuri Kaszubowski Lopes: Methodology, Software,

Validation, Writing - original draft, Investigation, Writing

- review & editing, Visualization. Peter Rockett: Conceptualization,

Methodology, Investigation, Writing - original draft, Writing

- review & editing, Supervision, Funding acquisition. Elizabeth

A. Hathway: Conceptualization, Methodology, Investigation,

Writing - review & editing, Supervision, Funding acquisition. Esmail

Saber: Software, Validation, Writing - review & editing,

Visualization.

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.

Acknowledgement

We gratefully acknowledge the financial support of the UK

Engineering and Physical Sciences Research Council (EPSRC) grant

EP/N022351/1.

References

[1] E.F. Camacho, C. Bordons, Model Predictive Control, second ed., Springer,

London, 2004.

[2] P. Rockett, E.A. Hathway, Model-predictive control for non-domestic buildings:

Critical review and prospects, Build. Res. Inf. 45 (5) (2017) 556–571,

http://dx.doi.org/10.1080/09613218.2016.1139885.

[3] G.P. Henze, Editorial – Model predictive control for buildings: A quantum

leap?, J. Build. Perform. Simul. 6 (3) (2013) 157–158, http://dx.doi.org/10.

1080/19401493.2013.778519, Special Issue on Model Predictive Control for

Buildings.

[4] M.A. Hussain, Review of the applications of neural networks in chemical

process control - simulation and online implementation, Artif. Intell. Eng.

13 (1) (1999) 55–68, http://dx.doi.org/10.1016/S0954-1810(98)00011-9.

[5] M. Wetter, Modelica library for building heating, ventilation and airconditioning

systems, in: F. Casella (Ed.), 7th International Modelica

Conference, Como, Italy, 2009.

[6] I. Hazyuk, C. Ghiaus, D. Penhouet, Optimal temperature control of intermittently

heated buildings using Model Predictive Control: Part I – Building

modeling, Build. Environ. 51 (2012) 379–387, http://dx.doi.org/10.1016/j.

buildenv.2011.11.009.

[7] D. Sturzenegger, D. Gyalistras, M. Morari, R.S. Smith, Semi-automated

modular modeling of buildings for model predictive control, in: 4th

ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in

Buildings (BuildSys ’12), Toronto, Canada, 2012, pp. 99–106, http://dx.doi.

org/10.1145/2422531.2422550.

[8] J. Sjöberg, Q. Zhang, L. Ljung, A. Benveniste, B. Delyon, P.-Y. Glorennec,

H. Hjalmarsson, A. Juditsky, Nonlinear black-box modeling in system

identification: A unified overview, Automatica 31 (12) (1995) 1691–1724,

http://dx.doi.org/10.1016/0005-1098(95)00120-8.

[9] O. Nelles, Nonlinear System Identification: From Classical Approaches to

Neural Networks and Fuzzy Models, Springer, Berlin, 2001.

[10] K.O. Stanley, R. Miikkulainen, Evolving neural networks through augmenting

topologies, Evol. Comput. 10 (2) (2002) 99–127, http://dx.doi.org/10.

1162/106365602320169811.

[11] B. Grosman, D.R. Lewin, Automated nonlinear model predictive control

using genetic programming, Comput. Chem. Eng. 26 (4–5) (2002) 631–640,

http://dx.doi.org/10.1016/S0098-1354(01)00780-3.

[12] Q. Feng, H. Lian, J. Zhu, Model predictive control of nonlinear dynamical

systems based on genetic programming, in: 36th Chinese Control Conference

(CCC), Dalin, China, 2017, pp. 4540–4545, http://dx.doi.org/10.23919/

ChiCC.2017.8028072.

[13] K. Rodríguez-Vázquez, C.M. Fonseca, P.J. Fleming, Identifying the structure

of nonlinear dynamic systems using multiobjective genetic programming,

IEEE Trans. Syst. Man Cybern. A 34 (4) (2004) 531–545, http://dx.doi.org/

10.1109/tsmca.2004.826299.

[14] M.P. Hinchliffe, M.J. Willis, Dynamic systems modelling using genetic

programming, Comput. Chem. Eng. 27 (12) (2003) 1841–1854, http://dx.

doi.org/10.1016/j.compchemeng.2003.06.001.

[15] G. Casella, R.L. Berger, Statistical Inference, Duxbury, Pacific Grove, CA,

2002.

[16] T. Dou, P. Rockett, Comparison of semantic-based local search methods for

multiobjective genetic programming, Genet. Program. Evol. Mach. 19 (4)

(2018) 535–563, http://dx.doi.org/10.1007/s10710-018-9325-4.

[17] R. Poli, W.B. Langdon, N.F. McPhee, A field guide to genetic programming,

2008, Published via http://lulu.com and freely available

at http://www.gp-field-guide.org.uk, http://dces.essex.ac.uk/staff/rpoli/gpfield-

guide/A\_Field\_Guide\_to\_Genetic\_Programming.pdf.

[18] J.R. Koza, Genetic Programming: On the Programming of Computers by

Means of Natural Selection, MIT Press, Cambridge, MA, USA, 1992.

[19] C. Fonseca, P.J. Fleming, Multiobjective optimization and multiple constraint

handling with evolutionary algorithms - Part I: A unified

formulation, IEEE Trans. Syst. Man Cybern. A 28 (1) (1998) 26–37, http:

//dx.doi.org/10.1109/3468.650319.

[20] R. Vyas, P. Goel, S.S. Tambe, Genetic programming applications in chemical

sciences and engineering, in: A.H. Gandomi, A.H. Alavi, C. Ryan (Eds.),

in: Handbook of Genetic Programming Applications, Springer International

Publishing, Cham, 2015, pp. 99–140.

[21] R. Pearson, Discrete-time Dynamic Models, Oxford University Press, 1999.

[22] J. Ni, R.H. Drieberg, P.I. Rockett, The use of an analytic quotient operator

in genetic programming, IEEE Trans. Evol. Comput. 17 (1) (2013) 146–152,

http://dx.doi.org/10.1109/TEVC.2012.2195319.

[23] T. Blochwitz, M. Otter, M. Arnold, C. Bausch, H. Elmqvist, A. Junghanns,

J. Mauß, M. Monteiro, T. Neidhold, D. Neumerkel, H. Olsson, J.-V. Peetz,

S. Wolf, C. Clauß, The Functional Mockup Interface for tool independent

exchange of simulation models, in: 8th International Modelica Conference,

Dresden, Germany, 2011, pp. 105–114, http://dx.doi.org/10.3384/

ecp11063105.

[24] D.B. Crawley, C.O. Pedersen, L.K. Lawrie, F.C. Winkelmann, EnergyPlus:

Energy simulation program, ASHRAE J. 42 (4) (2000) 49–56.

12

T. Dou, Y. Kaszubowski Lopes, P. Rockett et al. Applied Soft Computing Journal 97 (2020) 106695

[25] ASHRAE, Standard for the Design of High-Performance Green Buildings

Except Low-Rise Residential Buildings, Tech. Rep. ASHRAE 189.1, American

Society of Heating, Refrigerating and Air-conditioning Engineers, Atlanta

GA, 2009.

[26] CIBSE, CIBSE Guide A: Environmental Design, Tech. rep, The Chartered

Institution of Building Services Engineers, London, UK, 2015.

[27] T. Söderström, P. Stoica, System Identification, Prentice Hall, New York,

1989.

[28] T. Dou, Y. Kaszubowski Lopes, P. Rockett, E.A. Hathway, E. Saber, GPML:

An XML-based standard for the interchange of genetic programming trees,

Genet. Program. Evol. Mach. (2019) http://dx.doi.org/10.1007/s10710-019-

09370-4.

[29] J. Antonanzas, N. Osorio, R. Escobar, R. Urraca, F.M. de Pison, F. Antonanzas-

Torres, Review of photovoltaic power forecasting, Sol. Energy 136 (2016)

78–111, http://dx.doi.org/10.1016/j.solener.2016.06.069.

[30] D. Corne, A. Reynolds, S. Galloway, E. Owens, A. Peacock, Short term wind

speed forecasting with evolved neural networks, in: 15th Annual Conference

Companion on Genetic and Evolutionary Computation, Amsterdam,

The Netherlands, 2013, pp. 1521–1528, http://dx.doi.org/10.1145/2464576.

2482731.

[31] M.J. Powell, A direct search optimization method that models the objective

and constraint functions by linear interpolation, in: S. Gomez, J.-P. Hennart

(Eds.), in: Advances in Optimization and Numerical Analysis, Vol. 275,

Springer Netherlands, 1994, pp. 51–67, http://dx.doi.org/10.1007/978-94-

015-8330-5\_4.

[32] A.H.G. Rinnooy Kan, G.T. Timmer, Stochastic global optimization methods

part I: Clustering methods, Math. Program. 39 (1) (1987) 27–56, http:

//dx.doi.org/10.1007/BF02592070.

[33] A.H.G. Rinnooy Kan, G.T. Timmer, Stochastic global optimization methods

part II: Multi level methods, Math. Program. 39 (1) (1987) 57–78, http:

//dx.doi.org/10.1007/BF02592071.

[34] R.T. Clemen, Combining forecasts: A review and annotated bibliography,

Int. J. Forecast. 5 (4) (1989) 559–583, http://dx.doi.org/10.1016/0169-

2070(89)90012-5.

[35] A.R. Florita, G.P. Henze, Comparison of short-term weather forecasting

models for model predictive control, HVAC R Research 15 (5) (2009)

835–853, http://dx.doi.org/10.1080/10789669.2009.10390868.

[36] M. Gevers, Identification for control: From the early achievements to the

revival of experiment design, Eur. J. Control 11 (4–5) (2005) 335–352,

http://dx.doi.org/10.3166/ejc.11.335-352.

13