

MACHINE LEARNING-BASED PREDICTIVE BUILDING CONTROL SYSTEM AND METHOD

The present application claims priority to the Singapore patent application no. 10202102726W, the entire disclosure of which is incorporated herein by reference.

TECHNICAL FIELD

[0001] The present disclosure relates to the field of building automation and control systems, and more particularly to a system and method for predictive building control.

BACKGROUND

[0002] Building services are typically controlled in a piecemeal manner, for example, by individual occupants manually selecting a temperature set-point for the air-conditioning system in a room. A whole-building approach to building services control is challenging in many aspects, not least of which is the need to take into consideration the complex interplay between multiple factors such as room air temperatures, relative humidity, radiant temperature, air flow velocities, occupants' metabolic rates and clothing insulation, etc.

SUMMARY

[0003] In one aspect, the present disclosure provides a building control method to control an environment of a zone, the building control method comprising: acquiring real-time measurements related to the zone, the real-time measurements including at least two types of measurements; providing a linearized building dynamics model; and for a control interval, predictively determining an optimized output from optimizing a cost function based on the linearized building dynamics model, wherein the cost function is configured to simultaneously optimize two or more objectives, each of the objectives being determined by different types of the measurements; and using the optimized output to control at least one actuator operable in the zone, wherein the optimized output is one of a time series of optimized outputs determined based on the linearized building dynamics model, and wherein the optimized output corresponds to a combination of manipulated variables, each of the manipulated variables being configured to control a different one of the at least one actuator.

[0004] The building control method above, further comprising: for a model adaptation interval, using one or both of the real-time measurements and historical measurements to adapt a non-linear machine learning-based building dynamics model to obtain an adapted non-linear building dynamics model; and for each adapted non-linear building dynamics model obtained, applying linearization with feedback to linearize the adapted non-linear building dynamics model to obtain the linearized building dynamics model for use in optimizing the cost function at a subsequent control interval.

[0005] The building control method according to any described above, further comprising: at a selected control interval, using the real-time measurements to regenerate the linearized building dynamics model to obtain a regenerated linearized building dynamics model; and at the control interval following the selected control interval, optimizing the cost function using the regenerated linearized building dynamics model. Preferably, the regenerated linearized building dynamics model is regenerated at successive control intervals.

[0006] The adapted non-linear building dynamics model obtained at the model adaptation interval may be used to regenerate a plurality of the linearized building dynamics models, each of the plurality of the linearized building dynamics models corresponding to respective ones of the successive control intervals. The building control method may further include: after a first plurality of successive control intervals, performing a second adaptation of the adapted non-linear building dynamics model to obtain a second adapted non-linear building dynamics model; and using the second adapted non-linear building dynamics model to regenerate the linearized building dynamics model at each of a second plurality of successive control intervals. Preferably, the adapted non-linear building dynamics model is adapted at each of one or more adaption intervals, and wherein each of the one or more model adaptation intervals comprises a plurality of successive control intervals.

[0007] The building control method according to any described above, wherein the non-linear building dynamics model is based on a recurrent neural network with a non-linear autoregressive exogenous structure.

[0008] The building control method according to any described above, wherein the linearized building dynamics model is obtained by performing a Taylor's expansion for a given state vector.

[0009] The building control method according to any described above, wherein a process of linearizing to provide the linearized building dynamics model is characterized by an average processing time that is shorter than the control interval, and wherein the average processing time includes time for linearizing to obtain the linearized building dynamics model and for determining the optimized output. The control interval may be three orders of magnitude larger than the processing time.

[0010] According to another aspect, there is provided a building control system for controlling an environment of a zone, the building control system comprising: at least one model predictive control system is configured to: acquire real-time measurements related to the zone, the real-time measurements including at least two types of measurements; provide a linearized building dynamics model; and for a control interval, predictively determine an optimized output from optimizing a cost function based on the linearized building dynamics model, wherein the cost function is configured to simultaneously optimize two or more objectives, each of the objectives being determined by different types of the measurements; and using the optimized output to control at least one actuator operable in the zone, wherein the optimized output is one of a time series of optimized outputs determined based on the linearized building dynamics model, and wherein the optimized output corresponds to a combination of manipulated variables, each of the manipulated variables being configured to control one of the at least one actuator.

[0011] The model predictive system may be further configured to: for a model adaptation interval, use one or both of the real-time measurements and historical measurements to adapt a non-linear machine learning-based building dynamics model to obtain an adapted non-linear building dynamics model; and for each adapted non-linear building dynamics model obtained, apply instantaneous linearization with feedback to linearize the adapted non-linear building dynamics model to obtain the linearized building dynamics model for use in optimizing the cost function at a subsequent control interval.

[0012] The model predictive system may further be configured to: at a selected control interval, use the real-time measurements to regenerate the linearized building dynamics model to obtain a regenerated linearized building dynamics model; and at the control interval following the selected control interval, optimize the cost function using the

regenerated linearized building dynamics model. The regenerated linearized building dynamics model may be regenerated at successive control intervals. The adapted non-linear building dynamics model obtained at a first model adaptation interval may be used to regenerate a plurality of the linearized building dynamics models, each of the plurality of the linearized building dynamics models corresponding to respective ones of the successive control intervals. The model predictive control system may be further configured to: after the first plurality of successive control intervals, perform a second adaptation of the adapted non-linear building dynamics model to obtain a second adapted non-linear building dynamics model; and use the second adapted non-linear building dynamics model to regenerate the linearized building dynamics model at each of a second plurality of successive control intervals. The non-linear building dynamics model may be adapted at each of one or more model adaptation intervals, and each of the one or more model adaptation intervals comprises a plurality of successive control intervals.

[0013] The building control system according to any described above, wherein the non-linear building dynamics model is based on a recurrent neural network with a non-linear autoregressive exogenous structure. The building control system according to any described above, wherein the linearized building dynamics model is obtained by performing a Taylor's expansion for a given state vector. The building control system according to any described above, wherein the linearized building dynamics model is characterized by an average processing time that is shorter than the control interval, and wherein the average processing time includes time for linearizing to obtain the linearized building dynamics model and for determining the optimized output. The building control system according to any described above, wherein the control interval is three orders of magnitude larger than the processing time.

[0014] In another aspect, the present disclosure provides a building comprising: two or more building services sub-systems operable in one or more zones of the building, at least one of the two or more building services sub-systems being configurable by at least one actuator; at least one sensor disposed in the one or more zones; a machine learning-based model predictive control system is configured to: acquire real-time measurements from the at least one sensor, the real-time measurements including at least two types of measurements related to the one or more zones; provide a linearized building dynamics model; and, for a control

interval, predictively determine an optimized output from optimizing a cost function based on the linearized building dynamics model, wherein the cost function is configured to simultaneously optimize two or more objectives, each of the objectives being determined by different types of measurements; and use the optimized output to control the at least one actuator, wherein the optimized output is one of a time series of optimized outputs determined based on the linearized building dynamics model, and wherein the optimized output corresponds to a combination of manipulated variables, each of the manipulated variables being configured to control a different one of the at least one actuator.

[0015] The model predictive system may be further configured to: for a model adaptation interval, use one or both of the real-time measurements and historical measurements to adapt a non-linear machine learning-based building dynamics model; and at each control interval: perform linearization of the non-linear building dynamics model; and optimize the cost function to obtain the optimized output, wherein the model adaptation interval comprises a plurality of the control intervals. Adaptation of the non-linear machine learning-based building dynamics model may be responsive to a change in a configuration of the one or more zones. The adaptation may be performed not more than once every 24 hours, and wherein the linearization is performed at each control interval multiple times a day.

BRIEF DESCRIPTION OF DRAWINGS

[0016] Fig. 1 is a perspective view of a building with a building control system according to an embodiment of the present disclosure.

[0017] Fig. 2 is a schematic diagram of a building control system according to an embodiment of the present disclosure.

[0018] Fig. 3 is a schematic diagram of a machine learning model structure according to an embodiment of the present disclosure.

[0019] Fig. 4 is a schematic flowchart illustrating the building control method and system according to another aspect of the present disclosure.

[0020] Figs. 5 and 6 are schematic diagrams of an implementation of a building control system in an office according to an embodiment of the present disclosure.

[0021] Figs. 7 and 8 are plots illustrating measured indoor PMV according to the implementation of Figs. 5 and 6.

[0022] Figs. 9 and 10 are plots illustrating measured room air temperature according to the implementation of Figs. 5 and 6.

[0023] Figs. 11 to 12 are plots illustrating measured cooling power according to the implementation of Figs. 5 and 6.

[0024] Fig. 13 is a plot illustrating averaged daily cooling energy consumption according to the implementation of Figs. 5 and 6.

[0025] Fig. 14 is a plot illustrating effect of linearization on the performance of model prediction according to the implementation of Figs. 5 and 6.

[0026] Figs. 15 and 16 schematically illustrate methods of implementing embodiments of the model predictive control system in buildings.

[0027] Fig. 17 is a schematic diagram showing decentralized controlled architecture of implementing embodiments of the model predictive control system for multiple zones.

[0028] Fig. 18 is a schematic diagram showing centralized architecture of implementing embodiments of the model predictive control system for multiple zones.

DETAILED DESCRIPTION

[0029] Reference throughout this specification to “one embodiment”, “another embodiment” or “an embodiment” (or the like) means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment. Thus, the appearance of the phrases “in one embodiment” or “in an embodiment” or the like in various places throughout this specification are not necessarily all referring to the same embodiment. Furthermore, the described features, structures, or characteristics may be combined in any suitable manner in one or more embodiments. In the following description, numerous specific details are provided to give a thorough understanding of embodiments. One skilled in the relevant art will recognize, that the various embodiments be practiced without one or more of the specific details, or with other

methods, components, materials, etc. In other instances, some or all known structures, materials, or operations may not be shown or described in detail to avoid obfuscation.

[0030] The word “exemplary” is used herein to mean “serving as an example, instance, or illustration.” Any embodiment described herein as “exemplary” is not necessarily to be construed as preferred or advantageous over other embodiments. As used herein, the singular ‘a’ and ‘an’ may be construed as including the plural “one or more” unless apparent from the context to be otherwise.

[0031] Terms such as “first” and “second” are used in the description and claims only for the sake of brevity and clarity, and do not necessarily imply a priority or order, unless required by the context. The terms “about” and “approximately” as applied to a stated numeric value encompasses the exact value and a reasonable variance as will be understood by one of ordinary skill in the art, and the terms “generally” and “substantially” are to be understood in a similar manner, unless otherwise specified.

[0032] As will be evident from the various non-limiting examples below, embodiments of the present disclosure are useful in a wide range of applications, including but not limited to controlling an environment in a building or in specific zones of the building. The term “building” is used loosely in referring to a roofed and walled structure, and may be construed more broadly than the ordinary dictionary sense of the word. Examples of buildings to which embodiments of the present disclosure may be applied include but are not limited to high-rise buildings and skyscrapers, special purpose buildings such as hospitals or underground structures, both temporary shelters and permanent structures, structures for human habitation as well as for other uses like agricultural structures, climate-controlled enclosures, etc.

[0033] Fig. 1 illustrates an embodiment of a building control system 100 (or building services control system) deployed in a building 80 for environmental control. The building control system 100 includes one or more sensors 200 and one or more building environment actuators 300 (hereinafter referred to as “actuator” for the sake of brevity) disposed in, on, around, or in proximity to the building 80. The building control system 100 includes an on-site or remote model predictive control system 110 that is operably coupled or in signal communication with the one or more sensors 200 and the one or more actuators 300. The

one or more sensors 200 may include one or more humidity sensors, temperature sensors, lighting/brightness sensors, carbon dioxide sensors, etc. The one or more sensors 200 may further include one or more energy consumption meters, emission sensors, etc. The building 80 may have one or more heating, ventilation, and air-conditioning (HVAC) systems and/or air-conditioning and mechanical ventilation (ACMV) systems. The one or more actuators 300 may include one or more HVAC/ACMV actuators 310, light dimmers, controllable window shades or blinds 320, thermostats, dynamic facades, etc.

[0034] In some examples, one or more selected rooms/spaces 82/84 in the building 80 are provided with one or more sensors 200 while one or more selected rooms/spaces 84 in the building 80 are further provided with both one or more sensors 200 and actuators 300. Not all rooms/spaces 86 in the building 80 need to be provided with sensors 200 or building environment actuators 300. The building control system 100 may be deployed for the full interior space of one or more buildings 80, or for one or more specific connected or unconnected zones 88 of a building 80.

[0035] To aid understanding, a building control system 100 and method 102 according to one embodiment of the present disclosure will first be described in the following with respect to one zone 88 and with reference to the schematic diagram of Fig. 2, followed by showing the advantages arising from the application of the proposed system and method to an entire building and/or to multiple zones.

[0036] The building control system 100 includes a model predictive control system 110 configured to acquire measurements 208 related to building operations or environmental control of the zone 88. In some examples, the measurements 208 may be acquired from one or more of the sensors 200 monitoring the zone 88 and/or via feedback from one or more of the actuators 300 operable in the zone 88. In some examples, at least one sensor 200 or actuator 300 may provide a plurality of different types of measurements 208, such as providing both relative humidity measurements and temperature measurements. Preferably, the model predictive control system 110 receives at least two different types of measurements 208. In one non-limiting example, the model predictive control system 110 may acquire two different types of measurements 208 in the form of temperature readings and carbon dioxide measurements. In another non-limiting example, the model predictive

control system 110 may be configured to acquire three different types of measurements 208 in the form of air flowrate measurements, thermal energy meter measurements, and temperature sensor measurements. In yet another non-limiting example, the model predictive control system 110 is configured to acquire different types of measurements 208 from a combined temperature-and-relative humidity sensor, an air flowrate sensor, and a carbon dioxide sensor. The measurements 208 may include either or both measured disturbances 206 and measured outputs 204. Measured disturbances 206 include measurements of changes in the environment in the zone. Examples of measured disturbances 206 include but are not limited to internal heat load measurements, measurements of carbon dioxide concentration in the return air of the HVAC/ACMC system, measurements of weather conditions. Measured outputs 204 include but are not limited to measurements of the indoor conditions in the zone. Examples of measured outputs 204 include but are not limited to indoor thermal comfort or thermal discomfort.

[0037] The measurements 208 acquired by the model predictive control system 110 may first undergo preprocessing. The measurements may be stored in a database 210. For the purpose of the present disclosure, measurements that are acquired by the model predictive control system 110 at or near the time of measurement are referred to as real-time measurements 202. Measurements that are retrieved from the database 210 at a later time instant (relative to the time of measurement) are referred to as historical measurements 212. Real-time measurements 202 may be concurrently used at a current time step or a current control time interval as well as stored in the database 210 for use (as historical measurement 212) at a later time step or a later control time interval.

[0038] In an example where the proposed model predictive control system 110 is executed for the first time (initialization) for the zone 88, the model predictive control system 110 performs a step 140 of constructing a building dynamics model 142 based on historical measurements 212 and, optionally, both historical measurements 212 and real-time measurements 202. For the purpose of model construction 140, the required historical measurements 212 may be selected from the measurements 208 acquired over a relatively short period of time. In one non-limiting example, the model construction 140 uses historical measurements 212 and real-time measurements collected over the last 30 seconds immediately prior to or concurrent with the model construction 140. In another non-limiting

example, the model construction 140 is based on historical measurements 212 selected from measurements 208 acquired at various time instances over a 24-hour period. Using the proposed model predictive control system 110, it is not necessary to build a physics-based model to describe the building dynamics. It is also not necessary to collect months or seasons of data (as is required in conventional data-driven model training) before a building dynamics model can be built and used.

[0039] In some examples, a recurrent neural network (RNN) with nonlinear autoregressive exogenous (NARX) structure (NARX RNN) may be used to construct the building dynamics model 142 for the zone 88. Other network structures suitable for time-series prognostications may also be used to approximate the dynamics of the zone 88. In some examples, a Long Short-Term Memory (LSTM) network may be used. In some non-limiting examples, the model predictive control system 110 includes a model construction module 140 provided by a NARX RNN with feedback of outputs, as illustrated schematically in Fig. 3. The input variables 401 may include any combination of the following: Q_{clg} , f_{shade} , f_{lig} , C_{ra} , GHI , DHI and/or I_{inc} , which refer to the cooling power supplied by air conditioning (W), the shading level (%), the lighting dimming level (%), the carbon dioxide concentration in return air (ppm), the global horizontal irradiance (W/m^2), the diffuse horizontal irradiance (W/m^2), and the incident irradiance on the windows (W/m^2), respectively. The output variables 407 may include any one or more of the following: PMV_z , DGP_z and/or I_z , which refer to the indoor predicted mean vote (no unit), the indoor daylight glare probability (no unit) and the indoor illuminance (lux), respectively. The time delays 412 of the inputs 401 and the time delays 416 of the outputs feedback 409, as well as the number of neurons in the RNN hidden layer 403, may be determined by trial. The sigmoidal activation function 455, 495 may be employed in the respective hidden layer 403 and output layer 405 to the respective inputs and/or outputs feedback upon applying the respective weights 432, 436, 472 and biases 434, 474. The resulting building dynamics model 142 may also be referred to as a machine learning-based model 142.

[0040] The exemplary non-linear NARX RNN employed to approximate the dynamics of the zone 88 may be expressed by Equation (1) below:

$$y(t) = f(y(t-1), y(t-2) \dots y(t-n_{d,y}), u(t-1), u(t-2) \dots u(t-n_{d,u})), \quad (1)$$

where $y, f(), u, t$ and n refer to output, function, input, time, and number, respectively, and where the subscript d refers to the time delay.

[0041] The model predictive control system 110 linearizes 144 the machine learning-based model 142 to provide a linearized ML-based building dynamics model 122. Continuing with the example above, a state vector, x , is introduced to the non-linear NARX RNN to arrive at Equation (2) below:

$$x(t) = [y(t-1), y(t-2) \dots y(t-n_{d,y}), u(t-1), u(t-2) \dots u(t-n_{d,u})]. \quad (2)$$

[0042] At a time t , Equation (1) may be linearized around the measured current state ($x(t)$) using Taylor expansion .with the feedback of the measured current state. To predict the output at time $(t+1)$, Equation (1) becomes:

$$y(t+1) \cong f(x(t)) + \sum_{i=1}^{n_y} c_{y,i} (y(t-i+1) - y(t-i)) + \sum_{i=1}^{n_u} c_{u,i} (u(t-i+1) - u(t-i)), \quad (3)$$

$$\text{where, } c_{u,i} = \frac{\partial f(x(t))}{\partial u(t-i)}, \quad c_{y,i} = \frac{\partial f(x(t))}{\partial y(t-i)}.$$

[0043] Equation (3) is a linear approximation of the nonlinear NARX RNN model (Equation (1)) at the time step t .

[0044] Referring again to Fig. 2, the model predictive controller (MPC) 120 of the model predictive control system 110 is configured to search the optimized manipulated variables using a cost function 124, aiming to optimize or minimize multiple objectives represented in the cost function 124, deviation of the manipulated variables 112 from the performance goals 125, and violation of the constraints 126.

[0045] The MPC 120 is configured to generate a series of manipulated variables 112 (also referred to herein as target variable outputs). Each manipulated variable 112 is an optimized quantitative value corresponding to at least one performance goal 125. The manipulated variable 112 acts as a target for controlling at least one actuator 300 so as to effect changes

in the environment of the zone 88. Examples of manipulated variables 112 include but are not limited to cooling power set-points for the HVAC/ACMV systems, predicted mean vote (PMV) values, target relative humidity, target brightness, temperature, air velocity, mean radiant temperature, clothing level (of occupants), and metabolism rates (of occupants), etc.

[0046] The MPC 120 may be configured to take reference from at least one (environmental control-related) performance goal 125 of the zone 88. The at least one performance goal 125 may be preset or determined dynamically. In some embodiments, the cost function 124 includes multiple terms corresponding to a plurality of performance goals 125, such that the MPC 120 is optimized for multiple objectives. For example, the cost function 124 may have at least two performance goals 125 or objectives such as thermal comfort and energy savings. Examples of performance goals 125 include but are not limited to optimizing energy efficiencies and improving the thermal comfort of occupants, etc.

[0047] The cost function 124 may also be described as an objective function. Although embodiments of the present disclosure do not preclude the use of a linear cost function, various advantages of the present disclosure are more evident when the cost function is otherwise formulated so that it better reflects the nature of building control as a complex multi-variate problem. To illustrate, Equation (4) below describes an exemplary cost function 124 that may be employed in a model predictive controller 120 according to embodiments of the present disclosure.

$$J = \text{Minimize}(\sum_{k=1}^N Q_{clg,t+k}/sf + \sum_{k=1}^N [W_{PMV}(PMV_{t+k} - PMV_{ref})]^2 + W_{\epsilon}\epsilon_{t+k}^2), \quad (4)$$

which yields the constraints 126 as shown in Equation (5) below,

$$0 \leq Q_{clg} \leq Q_{cc}, -0.5 - \epsilon \leq PMV \leq 0.5 + \epsilon. \quad (5)$$

[0048] where symbols J is the objective, Q is the heat flow rate (Watt), sf is the scale factor, PMV is the PMV index, W is the penalty factor, N is the prediction horizon, and ϵ is the slack variable. Subscripts ref is the reference, clg is the cooling, cc is the cooling capacity, and k is the index of time steps. The three terms on the right side of Equation (4) represents the costs of cooling energy consumption, thermal discomfort, and constraints violation,

respectively.

[0049] In this non-limiting example, the cost function 124 is configured to search for an optimal manipulated variable 112 in the form of the cooling power set-points in the selected prediction horizon for a HVAC/ACMV system, while simultaneously taking into consideration the optimization of energy use in terms of the heat flow rate across the HVAC/ACMV fan coil unit as well as thermal comfort in terms of the predicted mean vote. The constraints 126 of indoor PMV may be set in a range of (-0.5, 0.5) to keep the environment in terms of thermal comfort within a range deemed comfortable for the intended occupants. More specifically, the reference PMV may be set at 0, corresponding to thermal neutrality. The applied constraints ensure that the maximum cooling power of the HVAC/ACMV system is kept below its cooling capacity. The scale factor of the cooling power of the HVAC/ACMV system is set as its cooling capacity. The penalty factors for thermal discomfort (W_{PMV}) and constraints (W_e) may be set at 4 and 10000, respectively. This setting drives the model predictive controller 120 to track thermal neutrality and to avoid violation of the constraints as much as possible as it seeks to minimize the cooling energy consumption. The control interval and prediction horizon may be set at 5 minutes and 12 control intervals, respectively.

[0050] Some actuators 300 may be directly controlled by the manipulated variables 112. In some examples, the operating parameters of the actuator 300 may be adjusted by a local controller 130. Upon communication of the manipulated variables 112 from the model predictive controller 120 to the local controller 130, the local controller 130 is configured to control the actuator 300 accordingly so as to change the environment of the zone 88. The local controller 130 may be a proportional–integral–derivative (PID) controller.

[0051] The MPC 120 may also be configured to periodically determine and update the at least one manipulated variable 112, and send the respective updated manipulated variable(s) to the respective actuators 300. For example, upon initialization, the MPC 120 may send the manipulated variables 112 generated for the first control interval to a local controller 130. The local controller 130 (which may be based on PID control) chases the manipulated variables 112 (e.g., cooling power set-points) by regulating the relevant actuators 300 (e.g., water valve and fan of the HVAC/ACMC systems). The real-time measured outputs 204

(e.g., indoor thermal comfort) and measured disturbances 206 (e.g., weather conditions and internal heat loads) of the building are fed back to the model predictive control system 110 and stored in the database 210.

[0052] For the subsequent control intervals, the model predictive control system 110 is configured to perform instantaneous linearization 144 of the non-linear building dynamics model 142 (acquired at the first control interval). In other words, the model predictive control system is configured to recurrently regenerate a linearized building dynamics model at each control interval. The model linearization 144 at each of the subsequent control interval may be based on real-time measurements 202. The real-time measurements 202 may include both the real-time measured outputs 204 and the real-time measured disturbances 206. The regenerated linearized building dynamics model 122 may be used to update the manipulated variables 112 at the control intervals. In one experiment, the manipulated variables can be updated as often as every five minutes when the model predictive control system of the present disclosure is implemented. In some embodiments, the linearized building dynamics model 122 may be regenerated according to a predetermined rule, such as periodically over a length of time and/or in response to one or more predetermined conditions being fulfilled. Regenerating the linearized building dynamics model 122 essentially results in an updated model predictive controller 122. In some embodiment, the regeneration of the linearized building dynamics model 122 may be synchronized with the updating of the at least one manipulated variable 112. In other embodiments, the regeneration of the linearized building dynamics model 122 is phase shifted from the updating of the at least one manipulated variable 112.

[0053] The model predictive control system 110 is further configured to adapt the non-linear building dynamics model 141 from time to time. Upon performing model adaptation 141, the adapted non-linear ML-based building dynamics model is linearized 144 to provide a linearized machine learning-based building dynamics model 122 for use by the MPC 120. Measurements 208 used for model adaptation 141 may include both real-time measurements 202 and historical measurements 212. Measurements 208 used for model adaptation 141 may include measured outputs 204 as well as measured disturbances 206. According to preferred embodiments of the present disclosure, for every one time that model adaptation 141 is performed, the adapted model 142 is used as the basis for regenerating linearized

models 122 at multiple control intervals. Model adaptation may be performed at model adaptation intervals, in which each model adaptation interval is preferably significantly longer than one control interval. To illustrate, in one non-limiting example, the model adaptation interval is 24 hours (to cover a full diurnal operation cycle of a building) and the control interval is 5 minutes (to enable fast or “real-time” response to varying disturbances and changes throughout the 24-hour period). In some embodiments, the model adaptation 141 may be triggered by a virtual timer. For example, the model adaptation 141 may be triggered at night for an office building or by seasonal changes.

[0054] In other words, at a selected control interval, real-time measurements are used to regenerate the linearized building dynamics model to obtain a regenerated linearized building dynamics model. At a control interval following the selected control interval, the cost function is optimized using the regenerated linearized building dynamics model. The regenerated linearized building dynamics model may be regenerated at every control interval. The adapted non-linear building dynamics model obtained at a first adaptation may be used to regenerate the linearized building dynamics model at each of a first plurality of successive control intervals. After the first plurality of successive control intervals, a second adaptation of the adapted non-linear building dynamics model may be performed to obtain a second adapted non-linear building dynamics model. Subsequently, the second adapted non-linear building dynamics model may be used to regenerate the linearized dynamics model at each of a second plurality of successive control intervals.

[0055] As shown above, the MPC 120 can account for multi-objective or multiple performance goals 125 (such as thermal comfort and energy saving). This coordinated or integrated optimization enables a coordinated control of multiple types of actuators (e.g., HVAC/ACMV systems and lighting systems), as opposed to piecewise and independent adjustments. Embodiments of the model predictive control system proposed herein can offer practical solutions for improving the building control of an old building. The building may be equipped with an old reactive control system. The old control system may include various sensors 200 and actuators 300, some of which are provided with local controllers 130. The building may be occupied, and it may be too disruptive, time-consuming, and costly to construct a physics-based model to upgrade the building control system. Preferably, the new/upgraded building control system can continue to leverage off the existing sensors 200

and actuators 300 to avoid wastage and to keep costs low. Fig. 4 illustrates a non-limiting example of a scheme 500 for implementing the proposed model predictive control system 110 in such buildings without the need to construct a physics-based model of the building dynamics.

[0056] Data may be acquired from the building's old control system 502, or otherwise collected 504, and stored in the database 210. The historical measurements available from the database 210 can be used to train/construct 140 a machine learning-based building dynamics model 142. The building dynamics model 142 is non-linear as it is configured to describe multiple types of performance goals and/or different types of manipulated variables in an integrated manner, including terms for non-linear behavior of environmental variables. The machine learning-based building dynamics model 142 is linearized 144 to provide a linearized building dynamics model 122. The MPC 120 (formulated 510 based on the linearized model 122) can be integrated with the rest of the existing building control system. For example, the manipulated variables 112 output from the model predictive controller 120 can be used in real-time control 530 of the existing actuators 300 and/or local controllers 130 of the existing actuators. The scheme 500 is characterized by at least two data feedback loops. One of the data feedback loops 540 feeds real-time measurements to adapt 141 the non-linear ML-based building dynamics model. Another one of the data feedback loops 550 feeds real-time measurements to regenerate the linearized building dynamics model 122 for a next control interval.

[0057] A test case using one embodiment of a proposed MPC 120 (MPC 120 according to an embodiment of the present disclosure) was compared against a conventional thermostat test case and a non-linear MPC test case. Fig. 5 illustrates a simplified layout of an office 600. The total floor area of the office is relatively small (100 m²), consisting of an open office area 602 and a meeting area 603. The open office area 602 has a seating capacity of 25 occupants. As the two areas 602,603 are connected through an open doorway 606, the entire space of the office 600 is considered as one thermal zone 88'. The open office area 602 is somewhat irregular in shape with two pillars 604, one open entrance 605, and one closable exit door 606. The exterior walls 608 of the office are 0.15-m-thick and are composed of concrete masonry units. There are 18 lighting fixtures (not shown) fitted on the ceiling with a power rating of 45 W each. Air-conditioning of the office is provided by

a fan coil unit (FCU) 700 illustrated schematically in Fig. 6. The FCU 700 consists of a cooling coil 702 having a total cooling capacity of 15 kW, and a constant air volume (CAV) fan 704 supplying $0.64 \text{ m}^3/\text{s}$ of conditioned air to the office 600 through four air diffusers 610 which are connected to the FCU 700 by air ducts 704. The primary air 730 supplied to the FCU 700 comes from a primary air handling unit (PAU) and its temperature varies from 25°C to 27°C in the experiments. Room air returns to the FCU 700 through two return grilles 612 and the ceiling air plenum. Prior to the experiment, the FCU 700 was solely controlled by a thermostat 630 manually adjustable by the occupants. The thermostat 630 is based on PID control and it regulates the flowrate of the chilled water 720 supplied to the cooling coil 702 through a motorized water valve 722 according to a set-point room air temperature between 22°C and 26°C (input by the occupants). The thermostat 630 also regulates the flowrate of the primary air 730 through a motorized air damper 732 according to a carbon dioxide concentration set-point of 700 ppm in the room air. Prior to the experiment, the FCU 700 was manually switched on in the morning and switched off in the evening by the occupants on workdays. The FCU 700 remained switched off during weekends and public holidays.

[0058] To implement the proposed model predictive control system 110 in the office 600, additional sensors 622, 624 were installed in the open office area and the ACMV system. A combined temperature-relative humidity sensor 622 and a globe temperature sensor 624 were installed in the open office area to measure the room air temperature, the relative humidity, and the globe temperature. These measurements are used for determining a level of indoor thermal comfort as represented by the PMV. Other variables which influence the PMV (such as air speed, occupant metabolic rate, and clothing level of the occupant) are assumed to be constant at 0.1 m/s , 0.57 met , and 1.2 clo , respectively. A thermal energy meter 740 is installed in the chilled water loop 720 of the FCU 700. The thermal energy meter 740 measures the supply and return temperatures as well as flowrate of the chilled water flowing through the cooling coil 702 to calculate the cooling power. Other sensors including combined temperature-relative humidity sensors 741, air flowrate sensors 742, and carbon dioxide sensors 743 were installed in the air loop of the FCU.

[0059] The architecture of the ML-based model used is as shown in Fig. 3. The cooling power, Q_{clg} , and the CO₂ concentration in return air, C_{ra} , are used as the inputs to predict

indoor PMV (measured output, MO). Q_{clg} is the manipulated variable (MV), and C_{ra} is the measured disturbance (MD) in the model predictive control system. Heat gains from other adjacent rooms, equipment, and lighting are considered as unmeasured disturbances. Occupancy load is represented by the carbon dioxide concentration in the return air. The inputs and outputs of the NARX RNN are summarized in Table 1 below.

Table 1. Inputs and outputs of the NARX RNN model for the office

	Variables	Variable type in the MPC system	Description
Inputs	Q_{clg}	MV	Cooling power supplied by FCU
	C_{ra}	MD	Carbon dioxide concentration in return air
Outputs	PMV	MO	Indoor PMV

[0060] Two weeks of historical building operations data, including the inputs and outputs of the NARX RNN model, were collected in the office 600 as it was controlled by its original thermostat for training an initial NARX RNN model. The data were collected by an I/O (input/output) system, which collected the data at 5-second intervals and stored the data in a server at 5-minute intervals. The cooling power, Q_{clg} , and the carbon dioxide concentration in return air, C_{ra} , were measured by the thermal energy meter 740 and carbon dioxide sensor 743. The indoor PMV is measured by the combined temperature-relative humidity sensor 622 and the globe temperature sensor 624. The historical measurements are randomly divided into three sub-sets along a timeline, i.e., 70% for model training, 15% for model validation, and the remaining 15% for model testing. The NARX RNN model was trained using Levenberg-Marquardt (LM) algorithm. The objective function used in the model training was to minimize the mean squared error (MSE) of the predicted indoor PMV against the measurements. Five neurons in the hidden layer were selected based on the trials. At this setting, the R-values of the initial NARX RNN model in the training, validation, and testing stages are 0.975, 0.974 and 0.977, respectively. The NARX RNN model was further updated continuously using online building operation data when the model predictive control system was controlling the office.

[0061] The three test cases with different controls for the FCU 700 were conducted in the office 600 and each case ran for 5 workdays. The testing on each day of the three cases was

from 8 am to 7 pm. The settings of the three cases are described in Table 2 below. The thermal comfort and energy efficiency performance of the three cases were evaluated using the measured indoor PMV and measured cooling power of the FCU, respectively. The two model predictive control cases ran on a typical laptop in the experiments.

Table 2. Settings of the test cases conducted in the office

Cases	Control system
Thermostat	Original thermostat of the office representing conventional reactive control.
Non-linear MPC	MPC using a non-linear machine learning-based (ML-based) building model
Proposed MPC	Proposed MPC using the linearized machine learning-based (linearized ML-based) building model

[0062] Fig. 7 shows the statistical distributions of the measured indoor PMV for each of the three test cases. Fig. 8 shows the time series of PMV over the course of one workday from 9 am to 6 pm. Fig. 9 shows the statistical distributions of the measured room air temperature. Fig. 10 shows the time series of the measured room air temperature over the course of the same day. A correspondence can be observed between the graphs of Fig. 7 and Fig. 9, and between the graphs of Fig. 8 and Fig. 10, as room temperature is related to the thermal comfort level. The PMV is based on a comprehensive thermal sensation model, and takes into consideration other factors besides room temperature. As with many factors and parameters in building control, there is no clear linear or directly proportional relationship between even such measurements as the PMV and the measured room air temperature.

[0063] Compared to the other control methods, the thermostat generally kept the office cooler throughout the day at a median room air temperature of 23.7 °C. Although the PMV remained within the “comfortable” range (-0.5, 0.5), the PMV was well below thermal neutrality (PMV = 0) throughout the day. This suggests that the office was overcooled. The median cooling power (Fig. 11) and the cooling energy consumption (Fig. 13) in the thermostat test case were significantly higher than the other two test cases. In addition, both the PMV and the temperature varied significantly throughout the period observed, as

indicated by an interquartile range (IQR) of the PMV of 0.19 and 0.57 °C, respectively. The large fluctuations are characteristic of a reactive control method.

[0064] The non-linear MPC (Conventional MPC / ML-based MPC) was able to maintain the PMV close to thermal neutrality ($PMV = 0$) throughout the day (Figs. 7 and 8), exhibiting the least amount of fluctuation in both PMV (Figs. 7 and 8) and measured room air temperature (Figs. 9 and 10). The improved performance of the non-linear MPC over the thermostat can be attributed to the predictive control enabled by the non-linear MPC. In terms of the cooling power (Fig. 11), the non-linear MPC shows a huge improvement equivalent to a 31.84% savings in cooling energy when compared against the thermostat (Fig. 13).

[0065] The test cases described above are based on one single zone of an office of 100 m² in floor space. To verify the practicality of implementing the non-linear MPC on a scale of a typical commercial building, a simulation was carried out for the non-linear MPC with a hypothetical office building with 60 thermally-independent zones, each served by a dedicated FCU. The non-linear MPC took 755.70 s of CPU (central processing unit) processing time to solve the non-linear optimization problem and obtain the optimal solutions for all the FCUs in the entire building. In other words, the non-linear MPC took more than 2 hours for each round of optimization, far longer than the intended control interval of 5 minutes. This means that the non-linear MPC would not be able to perform real-time building control.

[0066] Another simulation with similar conditions and constraints (commercial building with 60 thermally-independent zones each served by a dedicated FCU) was conducted using the machine learning-based MPC with instantaneous linearization was applied to. The machine learning-based MPC with instantaneous linearization took just 17.14 s of CPU processing time to obtain the optimal solutions for all of the FCUs, much less time than the control interval of 5 minutes. This represents an outstanding improvement in the computational load such that there is now a viable predictive controller for a real-time responsive building control system.

[0067] In another example, the linearized building dynamics model is characterized by an average processing time (average CPU processing time) that is shorter than the control

interval. The average processing time includes time for linearizing to obtain the linearized building dynamics model and for determining the optimized output. In one test, the control interval (300 s) was three orders of magnitude larger than the processing time (0.22 s).

[0068] Referring again to Figs. 7 to 10, it can be seen that the performance of the linearized MPC 120 test case is comparable to that of the non-linear MPC test case such that the multiple objectives of the building control system are not sacrificed for the sake of real-time responsiveness. The linearized MPC 120 was able to keep the PMV close enough to thermal neutrality such that, to the occupants, there would have been hardly any perceptible difference between the non-linear MPC and the linearized MPC 120 in terms of thermal comfort or room air temperature. The proposed linearized MPC 120 may be characterized by a median cooling power slightly higher than that of the non-linear MPC (Fig. 11), but the linearized MPC 120 (proposed MPC) nonetheless delivered a significant improvement equivalent to a 28.16% savings in cooling energy when compared against the thermostat (Fig. 13).

[0069] The effect of instantaneous linearization on the performance of model prediction is further analyzed. The distributions of absolute errors between the indoor PMV predicted by the two predictive models (the non-linear machine learning-based building dynamics model and the linearized machine learning-based building dynamics model) and the indoor PMV measured in the office are shown in Fig. 14. It is evident that the linearized machine learning-based building dynamics model (ML-based building model with IL) has comparable median, absolute, 25-percentile and minimum absolute errors relative to the machine learning-based building dynamics model (ML-based building model). Only the 75-percentile and maximum absolute errors of the linearized machine learning-based building dynamics model are slightly higher than the machine learning-based building model. This suggests that the instantaneous linearization does not degrade the model prediction performance in any tangible manner. The performance comparison shows that the proposed MPC 120 is able to significantly improve computational efficiency without sacrificing model accuracy or environmental control accuracy.

[0070] A computation speed comparison was done between a non-linear model predictive control system and the proposed model predictive control system 110 in the context of the

100 m² office test case. By using the same typical laptop for both of the predictive test cases, the CPU processing time for one optimization of the non-linear model predictive control system and the proposed model predictive control system 110 is 8.21 s and 0.03 s, respectively, demonstrating that the proposed model predictive control system 110 can significantly reduce the computation load by more than 200 times as compared to the non-linear MPC. With this reduction in the computational load required, the proposed model predictive control system 110 can afford to update the manipulated variables more frequently (compared to non-linear model predictive control systems) without over-burdening the building controls system. This translates to improved real-time response to changes that impact the real-time measured outputs and/or real-time measured disturbances. Additionally, the lighter computational load requirements also mean that the proposed model predictive control system 110 can be implemented in older buildings without the need for expensive overhaul of the existing hardware.

[0071] Embodiments of the proposed MPC 120 enable the configuration 104 of building control systems that are computationally light. This opens up opportunities to implement multiple environment control systems within one building without over-burdening existing computational hardware. Integrating the model predictive control system 110 with the existing building control system may include establishing a communication protocol with one of: an existing computing device, an existing processor, an existing set of computing instructions, etc. Examples of communication protocol (for communication of control commands 72 to the actuators and feedback 74 from sensors) include BACnet®, Niagara™, OPC®, LonWorks® and Modbus™, etc. The model predictive control system 110 may be embodied as a plug-in module, which communicates with the existing building control system 75 and the existing direct digital controller 77 (Fig. 15). Alternatively, for buildings that are not equipped with building automation controls (BAC), the proposed model predictive control system 110 can be coupled to the existing sensors 200 and actuators 300 via a direct digital controller 77 and essentially serve as the BAC system (Fig. 16). Whether a building comes without an existing BAC system or with a BAC system that can only handle relatively limited computational loads, the proposed model predictive control system 110 can be implemented without the need for major upgrades to the existing hardware of most buildings.

[0072] As shown in Fig. 17, according to one embodiment of the present disclosure, a building 80 may be segregated into multiple zones 88. The model predictive control system 110 may include multiple MPCs 120, each deployed in a respective zone 88. Under this decentralized control scheme 810, each MPC 120 controls a different zone 88 such that different parts of the same building 80 can enjoy differently customized environments.

[0073] Embodiments of the present disclosure enable the configuration 104 of building control systems without the need to construct physics-based building dynamics models. This enables the MPC 120 of the present disclosure to be quickly implemented in buildings where there is insufficient or a lack of building construction information (e.g., building materials heat absorption/reflection properties, physical dimensions, air flow patterns, dead air spaces, etc.) to construct a physics-based building dynamics model. It also enables the MPC 120 to accommodate zones of variable sizes/configurations. As illustrated in Fig. 18, one MPC 120 of the present disclosure may be implemented to control multiple zones 88 (in one or more interconnected buildings). Under such a centralized control scheme, the model predictive control system 820 may include at least one sensor and at least one actuator disposed in each of the zones. In one non-limiting example, the zones may represent rooms which can be joined together to form a large conference room, or divided off to form several separate meeting rooms. The non-linear machine learning-based building dynamics model can be adapted in response to a change of the configuration of the zones 88.

[0074] In some embodiments, the model adaptation 141 step may be automatically triggered, such that responsive to a predetermined rule or condition, the machine learning-based building dynamics model 142 is adapted. This provides an automated approach responsive to changes to the building. In other examples, the predetermined rule corresponds to a change in an environment outside of the building, such as a change of season or time of the day. The adaptation may be performed not more than once every 24 hours (e.g., during non-working hours), while the linearization may be performed multiple times throughout the day when the building is occupied. In another example, the predetermined rule corresponds to a change in the building dynamics of the building. Adaptation of the non-linear ML-based building dynamics model may be responsive to a change in a configuration of the one or more zones. Examples of a change in building dynamics include but are not limited to effects from: a changes in a volumetric space of building, changes in a room size

or a room configuration, changes in the operating performance, changes in the type and/or number of sensors and/or actuators, radiation level from the atmosphere, etc.

[0075] Building automation and control is a complex multi-variate problem. Optimization of a plurality of building performance parameters has to consider multiple competing objectives, such as thermal comfort of the occupants, energy consumption, etc. The environment in a building can be impacted by many factors, including but not limited to, temperature, pressure, brightness, noise, humidity, carbon dioxide content, oxygen content, vibration, etc. In addition, human activities and human traffic in and around the building also influence the building dynamics. Further, building dynamics also include effect from interactions between different sub-systems or different physical systems, such as heating and cooling system, ventilation system, lighting system. It may be appreciated that by increasing air flow in a cooling system will result in an increased in vibration and noise, which is an impact on the environment. Further, the increase air flow the cooling system results in heat produced in zones adjacent to the cooling system. Despite all the complexities of building control, the proposed MPC method 102 has been shown to be a viable alternative to the conventional reactive control method as well as the non-linear predictive control method. In particular, the proposed MPC method 102 is viable for a whole-building approach to managing these multiple factors. This is just one of the advantages of the proposed MPC method 102, which is characterized by a fast response time (completing optimization within a very short period of time of as short as a few seconds and/or about 200 times faster than other methods) while being configured to simultaneously optimize for multiple objectives in a manner that takes into account the complex influence of multiple building services sub-systems. For example, the HVAC/ACMC system may be one building services sub-system and the lighting system may be another building services subsystem.

[0076] In one aspect, the proposed MPC method 102 is configured to exploit a building dynamics model and measured/predicted disturbances (internal and external heat loads) to perform anticipation of future responses of the building. The proposed MPC 120 is configured to minimize a cost function to obtain the best control strategies in a prediction horizon with the model-based prediction capacity. The machine learning-based model 142 and hence the linearized building dynamics model 122 accounts for such interdependencies or spurious effects between the various building services sub-systems which are not

accounted for when building services sub-systems are considered independently. Disclosed herein is a building control system 100 which takes into account effect of various building services sub-systems, such as heating system, ventilation system, lighting system, and the interdependence between the sub-systems, to enable control over the building environment. The various interdependent relationships between the building services sub-systems may be non-linear, and are modeled by a single machine learning-based model according to embodiments of the present disclosure. This is a total departure from other proposals in which the data-based model requires each building services sub-system to be separately optimized by a respective sub-system model, i.e., one separately computed sub-system model for each specific building services sub-system.

[0077] In some embodiments, the machine learning-based building dynamics model 142 may be a control-oriented building model. The linearized building dynamics model 122 may receive measurements and output a predicted environment of the building. The linearized building model is able to predict an environment in the building based on current and projected measurements. It may be appreciated that the linearized machine learning-based building dynamics model 122 can take into consideration measurements of different nature, e.g., relating to heating, cooling, ventilation, humidity, etc., without the need to develop different sub-models for each type of measurement.

[0078] All examples described herein, whether of apparatus, methods, materials, or products, are presented for the purpose of illustration and to aid understanding, and are not intended to be limiting or exhaustive. Various changes and modifications may be made by one of ordinary skill in the art without departing from the scope of the invention as claimed.

CLAIMS

1. A building control method to control an environment of a zone, the building control method comprising:
 - acquiring real-time measurements related to the zone, the real-time measurements including at least two types of measurements;
 - providing a linearized building dynamics model; and
 - for a control interval, predictively determining an optimized output from optimizing a cost function based on the linearized building dynamics model, wherein the cost function is configured to simultaneously optimize two or more objectives, each of the objectives being determined by different types of the measurements ; and
 - using the optimized output to control at least one actuator operable in the zone, wherein the optimized output is one of a time series of optimized outputs determined based on the linearized building dynamics model, and wherein the optimized output corresponds to a combination of manipulated variables, each of the manipulated variables being configured to control a different one of the at least one actuator.
2. The building control method according to claim 1, further comprising:
 - for a model adaptation interval, using one or both of the real-time measurements and historical measurements to adapt a non-linear machine learning-based building dynamics model to obtain an adapted non-linear building dynamics model; and
 - for each adapted non-linear building dynamics model obtained, applying linearization with feedback to linearize the adapted non-linear building dynamics model to obtain the linearized building dynamics model for use in optimizing the cost function at a subsequent control interval.
3. The building control method according to claim 1 or claim 2, further comprising:
 - at a selected control interval, using the real-time measurements to regenerate the linearized building dynamics model to obtain a regenerated linearized building dynamics model; and
 - at the control interval following the selected control interval, optimizing the cost

function using the regenerated linearized building dynamics model.

4. The building control method according to claim 3, wherein the regenerated linearized building dynamics model is regenerated at successive control intervals.
5. The building control method according to any one of claims 2 to 4, wherein the adapted non-linear building dynamics model obtained at the model adaptation interval is used to regenerate a plurality of the linearized building dynamics models, each of the plurality of the linearized building dynamics models corresponding to respective ones of the successive control intervals.
6. The building control method according to any one of claims 2 to 5, further comprising:
after a first plurality of successive control intervals, performing a second adaptation of the adapted non-linear building dynamics model to obtain a second adapted non-linear building dynamics model; and
using the second adapted non-linear building dynamics model to regenerate the linearized building dynamics model at each of a second plurality of successive control intervals.
7. The building control method according to claim 2, wherein the adapted non-linear building dynamics model is adapted at each of one or more model adaptation intervals, and wherein each of the one or more model adaptation intervals comprises a plurality of successive control intervals.
8. The building control method according to any one of claims 1 to 7, wherein the non-linear building dynamics model is based on a recurrent neural network with a non-linear autoregressive exogenous structure.
9. The building control method according to any one of claims 1 to 8, wherein the linearized building dynamics model is obtained by performing a Taylor's expansion for a given state vector.

10. The building control method according to any one of claims 1 to 9, wherein a process of linearizing to provide the linearized building dynamics model is characterized by an average processing time that is shorter than the control interval, and wherein the average processing time includes time for linearizing to obtain the linearized building dynamics model and for determining the optimized output.
11. The building control method according to claim 10, wherein the control interval is three orders of magnitude larger than the processing time.
12. A building control system for controlling an environment of a zone, the building control system comprising:
 - at least one model predictive control system configured to:
 - acquire real-time measurements related to the zone, the real-time measurements including at least two types of measurements;
 - provide a linearized building dynamics model; and
 - for a control interval, predictively determine an optimized output from optimizing a cost function based on the linearized building dynamics model, wherein the cost function is configured to simultaneously optimize two or more objectives, each of the objectives being determined by different types of the measurements; and
 - using the optimized output to control at least one actuator operable in the zone, wherein the optimized output is one of a time series of optimized outputs determined based on the linearized building dynamics model, and wherein the optimized output corresponds to a combination of manipulated variables, each of the manipulated variables being configured to control one of the at least one actuator.
13. The building control system according to claim 12, wherein the model predictive system is further configured to:
 - for a model adaptation interval, use one or both of the real-time measurements and historical measurements to adapt a non-linear machine learning-based building dynamics model to obtain an adapted non-linear building dynamics model; and

for each adapted non-linear building dynamics model obtained, apply linearization with feedback to linearize the adapted non-linear building dynamics model to obtain the linearized building dynamics model for use in optimizing the cost function at a subsequent control interval.

14. The building control system according to claim 12 or claim 13, wherein the model predictive system is further configured to:

at a selected control interval, use the real-time measurements to regenerate the linearized building dynamics model to obtain a regenerated linearized building dynamics model; and

at the control interval following the selected control interval, optimize the cost function using the regenerated linearized building dynamics model.

15. The building control system according to claim 14, wherein the regenerated linearized building dynamics model is regenerated at successive control intervals.

16. The building control system according to any one of claims 13 to 15, wherein the adapted non-linear building dynamics model obtained at the first model adaptation interval is used to regenerate a plurality of the linearized building dynamics models, each of the plurality of the linearized building dynamics models corresponding to respective ones of the successive control intervals.

17. The building control system according to any one of claims 13 to 16, wherein the model predictive control system is further configured to:

after a first plurality of successive control intervals, perform a second adaptation of the adapted non-linear building dynamics model to obtain a second adapted non-linear building dynamics model; and

use the second adapted non-linear building dynamics model to regenerate the linearized building dynamics model at each of a second plurality of successive control intervals.

18. The building control system according to claim 13, wherein the non-linear building dynamics model is adapted at each of one or more model adaptation intervals, and wherein each of the one or more model adaptation intervals comprises a plurality of successive control intervals.
19. The building control system according to any one of claims 12 to 18, wherein the non-linear building dynamics model is based on a recurrent neural network with a non-linear autoregressive exogenous structure.
20. The building control system according to any one of claims 12 to 19, wherein the linearized building dynamics model is obtained by performing a Taylor's expansion for a given state vector.
21. The building control system according to any one of claims 12 to 20, wherein the linearized building dynamics model is characterized by an average processing time that is shorter than the control interval, and wherein the average processing time includes time for linearizing to obtain the linearized building dynamics model and for determining the optimized output.
22. The building control system according to claim 21, wherein the control interval is three orders of magnitude larger than the processing time.
23. A building comprising:
 - two or more building services sub-systems operable in one or more zones of the building, at least one of the two or more building services sub-systems being configurable by at least one actuator;
 - at least one sensor disposed in the one or more zones;
 - a machine learning-based model predictive control system is configured to:
 - acquire real-time measurements from the at least one sensor, the real-time measurements including at least two types of measurements related to the one or more zones;
 - provide a linearized building dynamics model; and

for a control interval, predictively determine an optimized output from optimizing a cost function based on the linearized building dynamics model, wherein the cost function is configured to simultaneously optimize two or more objectives, each of the objectives being determined by different types of the measurements; and

use the optimized output to control the at least one actuator, wherein the optimized output is one of a time series of optimized outputs determined based on the linearized building dynamics model, and wherein the optimized output corresponds to a combination of manipulated variables, each of the manipulated variables being configured to control a different one of the at least one actuator.

24. The building of claim 23, wherein the model predictive system is further configured to:

for a model adaptation interval, use one or both of the real-time measurements and historical measurements to adapt a non-linear machine learning-based building dynamics model; and

at each control interval:

perform linearization of the non-linear building dynamics model; and

optimize the cost function to obtain the optimized output, wherein the model adaptation interval comprises a plurality of the control intervals.

25. The building of claim 24, wherein adaptation of the non-linear machine learning-based building dynamics model is responsive to a change in a configuration of the one or more zones.

26. The building of claim 25, wherein the adaptation is performed not more than once every 24 hours, and wherein the linearization is performed at each control interval multiple times a day.