Zone-level Agreement by Consensus for Building Thermal Energy Management

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Abstract— **The paper addresses the problem of distributed agreement for control of building thermal energy through a class of consensus algorithms. The context of the work is defined by the emergence of dense networked measurement and control systems and the cyberphysical paradigm in real world building energy management applications. This has occurred more saliently by means of wireless sensor network systems, offering integration of sensing, computing and actuation capabilities. Key point is mitigation of current model- and occupancy-based strategies in order to increase building energy efficiency under a unifying framework. We consider both convergence and convergence speed conditions and relate our approach to the state-of-the-art. Simulation results are presented on a reference multiple thermal zone model.**

I. INTRODUCTION

Building energy efficiency represents a key area of interest from an environmental and economic perspective, given the impact of up to 40% that buildings have in the total energy consumption of a country. Optimal management of energy resources within buildings brings upon considerable benefits also at the grid level by diminishing the environmental impact of peak power capacity along with the associated energy costs. Given the importance of the field, it has attracted contributions from various areas of research such as: electrical and control engineering, computer science and civil engineering. From the control perspective, modern buildings are densely intrumented with smart sensors, actuators and controllers linked together by dedicated communication buses, using etiher proprietary or open hardware/software architectures e.g. SMAP [1]. Control loops are implemented using either conventional PID or more modern, but more complex and model-sensitive, MPC strategies [2]. On the other hand, older and existing building pose a relevant use case for wireless networked sensing and actuation which can help mitigate the costs in deploying and maintaining intelligent building technology [3]. The current paper is focused on consensus and optimization for building thermal energy management including by leveraging the personal profiles and social interactions among building users as external inputs for the global system model. The proposed solution is suitable for both centralized and decentralized implementations.

For the purpose of the current contribution, two alternative approaches are described. We have observed how to improve model-based control with human feedback and robust occupancy information (e.g. performing system identification of the current data sets and obtaining realistic discomfort functions). Also, from the opposite perspective, a novel method would assume improving control based on human feedback with a model-based approach which can mitigate some of the drawbacks, such as incomplete, inconsistent information.

Previous contributions have proposed and illustrated the application of consensus for building energy management through agreement between the user and a central controller [4]. In this approach it is assumed that the users of the building have a direct economic stake in the operation of the building. Thus, they react to energy signals sent by the controller in order to accomodate a decrease in comfort for economic benefits. Distributed consensus for a common temperature set-point at the zone level is thus achieved, which minimizes a global cost-comfort objective function.

Based on this view, acknowledging the interesting applications that might arise from the combination of distributed sensing and intelligent control via consensus mechanisms, we discuss an alternative approach. This relies on the idea of local, zone-level consensus upon temperature set-points, under a global cost-only constraint. The mechanism relies on user preference feedback and is suitable for centralized and decentralized implementations. It can be implemented by exploiting ”dead-zones” i.e. non-convex ranges in the individual discomfort curves, where the users are insensitive to temperature changes. The second option is to carry out a trade-off mechanism for inter-zone agreement where some zones accept a temporary decrease in comfort for the well-being of others, under the global cost constraint. Occupant feedback is weighted against a range of parameters which consider, among others: the proportion of time associated with a certain zone, the feedback activity and interaction with other users, as well as the statistical relevance among the user pool.

The paper is structured as follows. Section 2 lists the key underlying concepts allowing the analysis and deployment of consensus mechansims for pervasive building energy management. Section 3 presents our appoach for system modeling and methodology, using current available tools, aimed at collaborative agreement for zone-level temperature set points under rigid cost constraints. A consensus case study

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is detailed and simulation results, quantifying the impact of heat exchange through various wall models, are discussed in Section 4. This is based on a realistic building model where previous work was concerned with model-predictive control and occupancy- based methods for increasing energy efficiency. The conclusion section illustrates future steps towards implementation and experimental evaluation.

II. CONSENSUS BACKGROUND AND RELATED WORK

Historically, consensus methods were developed as a suitable way to implement distributed agreement among groups of intelligent "agents" which can compute and communicate. What provides the main attraction for this class of algorithms is the strong background of results stemming from graph and matrix theory. This provides a basis for guiding convergence towards a desired outcome in what concerns both the convergence value and convergence speed. Applications have emerged in distributed sensor fusion, autonomous vehicle control and cooperative systems.

Formal consensus theory assumes a graph representation $\mathcal{G}(\mathcal{V},\mathcal{E})$ with the node set $\mathcal{V} = 1,2,...,N$ and edges $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$. This represents a model of the underlying network structure or communication topologies. From the basic undirected model, the analysis has been extended towards directed, model of assymetric links, and time-varying links, accounting for stochastic communication losses. The continuous time consensus algorithm and update law for node n_i is conventionally expressed as:

$$\dot{x}_i(t) = -\sum_{j=1}^{n} a_{ij}(t)[x_i(t) - x_j(t)] \quad (1)$$

In discrete form, more suitable to event-based systems prone to periodic communication among nodes, we have:

$$x_i[k+1] = -\sum_{j=1}^{n} d_{ij}(k)[x_i(k) - x_j(k)] \quad (2)$$

The Laplacian matrix L is defined as the subtraction of the diagonal degree matrix of the graph D and the adjacency matrix A:

$$L = D - A \quad (3)$$

Fundamentals of consensus algorithms have been established in [5], [6]. Convergence is evaluated thorugh graph connectivity properties in both directed and undirected cases. An indication of algorithm convergence speed is given by evaluating the second-smallest eigenvalue of the Laplacian. This has lead to the pursuit of optimization of graph weights to achieve fastest possible agreement [7], while shaping the network structure. Dynamic, time-varying communication topologies can also be accounted for in realistic modeling of uncertainity in radio links. [8] studies the impact of various graph topologies on local average consensus achievement and convergence rate. Main result is that a small-world topology is desirable for efficient information passing and agreement. A thorough review of the main theoretical results of consensus algorithms for control is carried out in [9].

In [10] the authors describe the design of a new adaptive protocol for a leader-follower multi-agent scenario. The agents posess nonlinear dynamics given by $\dot{x}_i = x_i^2 + u_i$ and the methods is proven to provide optimal construction of the parameter update and control laws for agreement to the leader dynamics under control. The problem assumes a directed and strongly connected communication graph. The logarithmic quantization strategy for sampled systems is discussed by [11]. Main improvement consists of the analysis associated to the bound for sample time and sampling parameter in the case of first order integratror dynamics, along with a numerical example for a four agent network. The consensus problem for non-identical coupled agents is discussed in [12]. The authors use the left eigen vector of the Laplacian matrix, associated to the zero eigenvalue, to establish a Lyapunov function used in exploring the boundedness of the agreement.

An application to distributed estimation in sensor networks by means of consensus is presented in [13]. Both time invariant and random switching topologies are investigated by means of a LQR approach and estimation error results are ilustrated. A method for selecting the best control gains for fast finite-time consensus is given in [14]. For a simple network of agents with unmodelled dynamics and unknown disturbance, tracking performance is evaluated and shown to achieve finite-time consensus. Finally, in [15] both fixed and switching topology cases are studied for consensus networks in the presence of distance-dependant multiplicative noise, using a sound approach to design the consensus gain which guarantees convergence.

In what concerns applications to building thermal energy management. The authors of [16] propose consensus-based modeling of zone interactions for thermal control. Main improvement consists of replacing static link weights with transfer functions which dynamically model thermal energy transfer between adjacent zones. This has been expressed as:

$$\Xi_i(s) = -\frac{1}{s}\sum_{j \in N_i} [\lambda_{ij}^S(s)\Xi_i(s) - \lambda_{ij}^C(s) - \Xi_j(s)] \quad (4)$$

with the weights in the consensus model being replaced by $\lambda_{ij}^S(s)$ and $\lambda_{ij}^C(s)$ as self-correction and cross-correction terms for node n_i, as real rational transfer functions. The basic assumption defining the temperature dynamics based on the heat fluxes among adjoining thermal zones is described as:

$$T_i(s) = -\frac{1}{C_i^r s}[\frac{A_{ij}(s)}{B_{ij}(s)}T_i(s) - \frac{D_{ij}(s)}{B_{ij}(s)}T_j(s)] \quad (5)$$

For the contribuion in [16] a 3R2C model is employed but this can be adjusted and also external heat fluxes which influence the system can be subsequently introduced via disturbance channels. A more detailed overview of thermal network modeling for building automation and control systems can be found in [17]. Thermal modeling and control in [4], [18] uses bi-directional exchange of messages between individual users of a building and a central controller in order to agree upon optimal zone-level temperature references. The method is sound from an optimization perspective but a drawback of this approach is that is assumes that the users have a stake in economic operation of the building and cost reduction which might not be feasible in a real scenario.

Acknowledging previous and current work, our contribution is focused on addressing the building thermal energy control problem by means of consensus algorithms and system modeling using conventional RC networks, suitable to be enhanced with occupant comfort and feedback functions via external signals.

III. SYSTEM MODELING AND METHODOLOGY

Our approach combines classic MPC control with consensus network modeling of the thermal zones while allowing the inclusion of disturbances related to both external heat fluxes and human behaviour. This discrete MIMO system is illustrated in Figure 1:

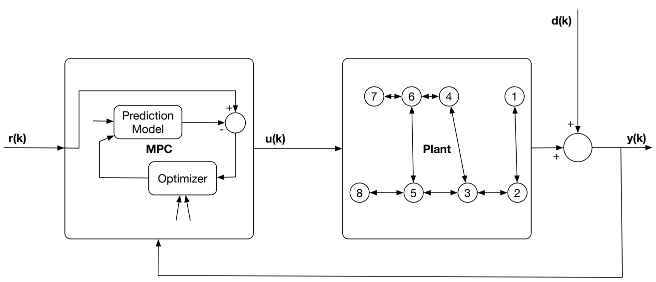

Fig. 1. System modeling for control

where the reference signal $r(k)$ contains the desired temperature set-points for each of the thermal zones and $u(k)$ is the command signal, as output of the MPC control block. The disturbance signal $d(k)$ is applied at the output of the plant, modeled as a dynamic consensus thermal network, and mainly accounts for the interaction between the building and the outside environment at the external boundaries. The output $y(k)$ is used to close the loop and update the prediction-optimization mechanism at each sampling period via receding horizon control. Internal to the MPC block, there is the need to define previous plant behaviour and outputs as well as the global cost and constraints functions. Constraints are used to set feasible limits on the output in regard to physical or operational limitations, such as bounds on control signals and associated rate of change or other electrical and mechanical bounds of the plant.

The MPC strategy has been well adopted by industry for process control and more recently its application has been extended to building energy management for a broad class of solutions and experimental test-beds [2]. Key point is achieving a tradeoff between extensive high order building modeling and simplified representations which are feasible for control design. The methods range from physical detailed modeling of construction properties and dynamics to black-box input-output system identification, passing through grey box methods which combine the two. Conventional formulation of MPC relies on a multi-variable discrete state-space system representation as:

$$x[k+1] = Ax[k] + Bu[k] \tag{6}$$

$$y[k] = Cx[k] + Du[k] \tag{7}$$

In our particular case, the model of the HVAC system accounts for both the primary air loop and zone-level variable air volume units as terminals. A modular approach enables the separation between core thermal dynamics of the building, external influences and disturbances. The full discrete, mildly non-linear (bi-linear) model is expressed as:

$$\begin{aligned} x[k+1] = Ax[k] + B_u u[k] + \sum_{i=1}^{n_u} B_{xui} x[k] u_i[k] + \\ + B_v v[k] + \sum_{i=1}^{n_v} B_{vui} v[k] u_i[k] + d[k] \end{aligned} \tag{8}$$

This is accompanied by an objective function, being subject to minimization:

$$J = \sum_{k=0}^{N-1} q(k)(y(k) - z(k))^2 + r(k)u(k)^2 \tag{9}$$

under a series of constraints:

$$u_{min} \leq u(k) \leq u_{max} \tag{10}$$

$$y_r(k) \leq z(k) \tag{11}$$

$$\delta_{max} \geq |u(k) - u(k-1)| \tag{12}$$

It can be seen how, for large buildings i.e. large number of thermal zone, with complex constraints given by process dynamics and construction and HVAC system properties, the control solution becomes difficult to compute at reasonable sampling times. One alternative is to formulate building thermal control based on layers: local, central and optimization layers. In parallel, include disturbances such as external influence, user habits and comfort and cost constraints and define as main control objective: guide the natural convergence and consensus to desired state while accounting for these external influences.

Typically the main tool for building modeling across a range of engineering domains has been the Energy+ environment, which allows detailed representations of construction characteristics, mechanical and electrical loads as well as external weather forecast models. An example on how to bridge the simulation environment towards more suitable environments for control design, the BRCM [19] toolbox can be used to generate the discrete state-space representation in matrix form, along with cost and constraint matrices. This allows for control design and simulation in an integrated environment such as Matlab/Simulink. Figure 2 illustrates the graphical outcome of the conversion of an existing Energy+ model via BRCM, for a real facilities building from our campus. One step further, occupancy models have been included in the system model [20] with show significant energy saving potential.

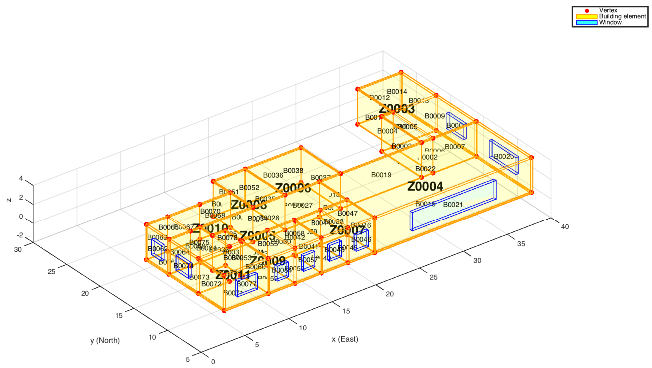

Fig. 2. Graphical building representation for thermal control

For practical data acquisition and command, the current system uses an SMAP middleware platform which operates as bridge between the commercial grade BMS system: controller, sensing and actuating units, software, etc. This allows for multi-vendor integration under a pre-defined API for collecting data and handling requests and accounting for future scalability. In our case zones are conditioned using a central air heating and cooling system with variable air volume (VAV) units assigned to each thermal zone. For our framework a VAV represents both the sensor and actuator at the zone level and receives the desired set-point from the central MPC controller, using a local PID control loop to achieve it. VAV fields include: 50% CFM Alarm, 70% CFM Alaerm, Airflow Request, CD Static Request, Cool Request, Cool Stpt, DA Temp 10 degf Lo Alarm, DA Temp 5 degf Lo Alarm, **Damper Position**, **Discharge Temp**, Flow Control, HW Valve, Heat Request, Hi Zone Temp 2F, Hi Zone Temp 4F, Local Override, Low Zone Temp 2F, Low Zone Temp 4F, Mode, Run, Run Request, **Zone Temp**.

IV. CASE STUDY

We present simulation results on a consensus network of eight thermal zones, modeling a part of a real campus building. Table 1 lists the essential characteristics for the first modeling stage which accounts for the zone size and interconnection to other zones. A thermal zone is an air volume assumed to have constant temperature which is associated to a single heating/cooling local unit, a VAV in our case. Thus, we observe various situations where: a zone represents a single room, a zone spans multiple smaller rooms or hallways and finally, larger areas are split into different thermal zones. In the latter case, the thermal resistance across the zone boundary is considered to be zero, allowing direct bi-directional heat flow between the zones. The main simplifying assumption for this case is that we consider the thermal zone network in isolation from the external environment and neighboring internal zones i.e. external walls have infinite thermal resistance.

TABLE I
ZONES

Thermal zone	Sqft.	Connected with
Zone 1	404	Z2
Zone 2	727	Z1, Z3
Zone 3	727	Z2, Z4, Z5, Z6
Zone 4	395	Z3, Z6
Zone 5	500	Z3, Z6, Z8
Zone 6	535	Z3, Z4, Z5, Z7
Zone 7	295	Z6
Zone 8	200	Z5

Zone delimitation overlayed on top of the reference floor plan is illustrated in Figure 3. Our approach is scalable i.e. it is easy to include more zones in the simulation, having all the data available, while accounting for simulation and control time.

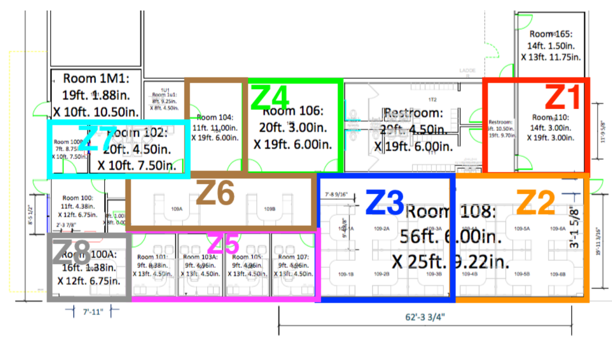

Fig. 3. Zone layout

By means of large scale system and subsystem modeling we are able to implement the simulation illustrated in Figures 4 and 5 which accurately represents the dynamic consensus network corresponding to the plant model from the previous section. Each node corresponds to a thermal zone, with integrator dynamics accounting for the heat capacity of the uniform temperature air volume, weighted by the zone surface at constant height. From this point, we are able to parametrize room and interconnection models as well as use the same environment for control design and simulation.

Initial results are presented in Figure 6 which reflect how each zone temperature progresses to the equilibrium point i.e. consensus value. For intialization we use the current state variables, temperatures in Fahrenheit degrees, which are queried in real-time from the middleware server. Given that the underlying directed graph topology is connected, agreement is achieved.

Enhanced results account for the introduction of the wall model into the simulation. It can be seen how this impacts consensus convergence especially related to convergence speed which becomes at least an order of magnitude slower. Following wall models have been evaluated: R, RC and 3R2C respectively. Constant values are derived from material properties and other physical characteristics that can either be embedded into the original building model or dynamically adjusted at the simulation run-time.

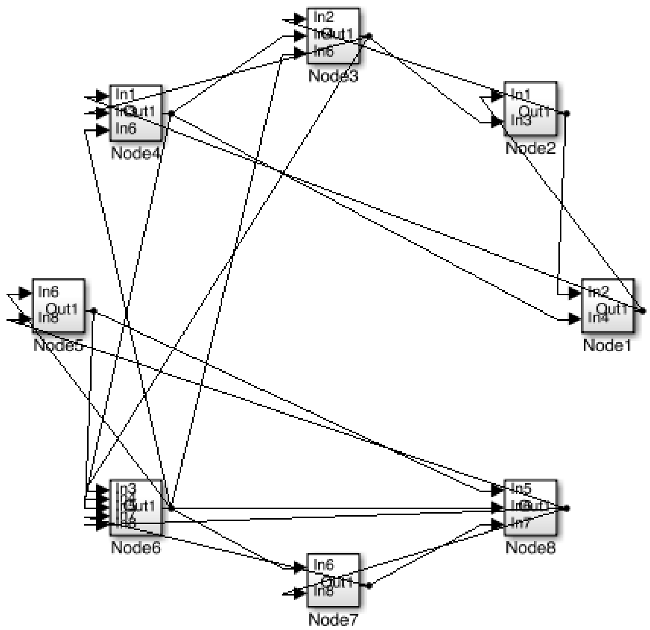

Fig. 4. Thermal network for consensus modeling: network level

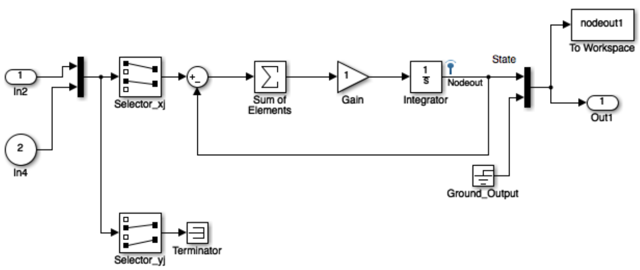

Fig. 5. Thermal network for consensus modeling: node level

Figure 8 presents the final results, using higher order dynamics for the wall model. These correspond to a multi-layer wall model that both hinders the heat transfer across zones/rooms and accumulates heat within the layers via the resistance-capacitance analogy.

Finally, we plot the root mean squared error (RMSE) evolution among the individual zone temperatures and the final consensus value for each of the three simulation experiments. RMSE at each simulation step is computed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(T_i - c)^2}{n}} \tag{13}$$

where T_i is the current temperature of zone i and c is the final consensus temperature for the eight zones at the end of the simulation.

The outcome of the comparison is illustrated in Figure 9 for the baseline, enhanced and higher order (HO) models. Convergence and convergence speed can be comparatively assessed via this graph.

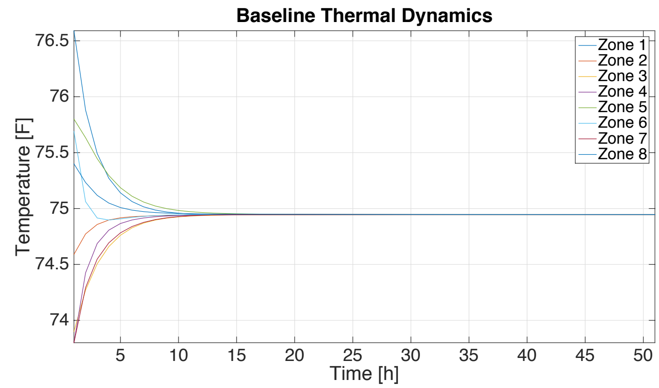

Fig. 6. Thermal consensus dynamics

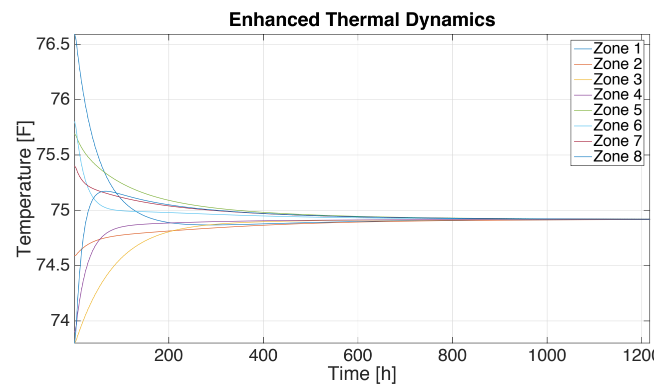

Fig. 7. Thermal consensus dynamics incl. wall model

V. CONCLUSION

The paper presented a new approach aimed at combining classic MPC strategies with a dynamic consensus network model in order to improve the efficiency of thermal processes within buildings. Initial simulation results have been illustrated and discussed along with the pathways towards implementation on a real building using appropiate integration with the BMS system via dedicated middleware such as SMAP.

Consensus models allowed leveraging intuitively the interconnection among the thermal zones of the building while allowing extensions towards a full control framework. This accounts mainly for the closed-loop control using MPC but also involving stakeholders such as the users of the building and facilities managers to influence the process towards energy savings and/or comfort.

Current and future work is focused on human-in-the-loop enhancements by deriving suitable transfer functions by non-parametring modeling. This is aimed at captureing human behaviour patterns and feedback in order to improve the control performance under given cost constraints. The approach is feasible to both new, densely instrumented, buildings as well as for existing buildings which can make use of wireless sensor and actuator network (WSAN) [21] deployments.

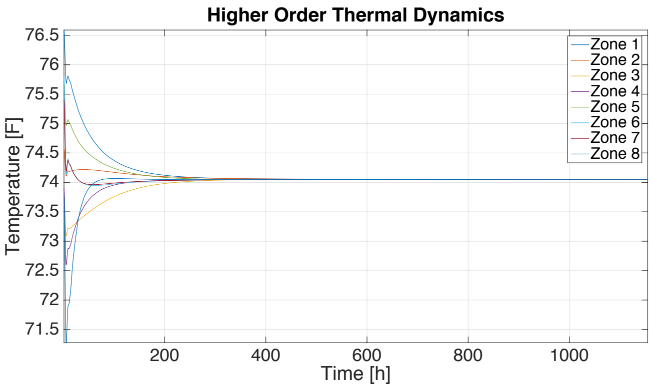

Fig. 8. Thermal consensus dynamics with higher order wall modell

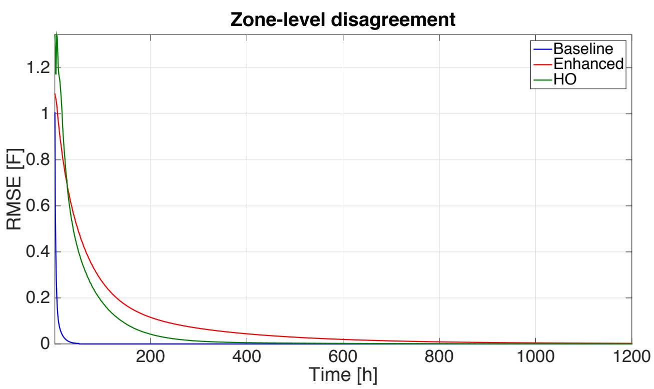

Fig. 9. Comparative analysis by means of RMSE

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