Flexible Piecewise Function Evaluation Methods Based on Truncated Binary Search Trees and Lattice Representation in Explicit MPC

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***Abstract*—Efficient methods for evaluation of piecewise functions defined over convex polyhedral partitions are proposed. As an important application, the explicit model predictive control problem is considered which requires a piecewise affine (PWA) control law to be evaluated online. The widely used Binary Search Tree (BST) method is modified to be able to deal with a wider class of problems for which the BST method becomes prohibitive in terms of preprocessing time or memory requirements. The proposed method combines an Orthogonal Truncated Binary Search Tree (OTBST) and lattice representation for PWA functions in a unified structure enjoying the advantages of both approaches. Both OTBST and Lattice-based OTBST (LOTBST) methods enable the designer to trade-off between preprocessing time, storage requirement and online computation time. The OTBST approach can be applied to more general partitions, e.g. discontinues and overlapping, while the LOTBST is directed towards more efficient evaluation of PWA functions, associated to the explicit MPC solutions. The key feature of the proposed methods is that the exact solution can be computed with predefined worst case online computation time guarantees. The computations are readily implementable using fixed-point arithmetic on a low cost microcontroller since there is no recursive accumulation of round-off errors, and the online algorithm is simple with a small footprint suitable for formal verification of correctness of implementation. Using several examples it is shown that the proposed LOTBST leads to a considerably less preprocessing time and memory requirement comparing to the pure BST and less online computation time comparing to the pure lattice representation.**

***Index Terms*—Piecewise Function Evaluation, Piecewise Affine Functions, Explicit Model Predictive Control, Lattice Representation, Binary Search Tree.**

I. Introduction

Piecewise functions have received significant attentions over the last few years and in most of the applications efficient evaluation of the piecewise function is a crucial problem especially when there is a large number of function pieces. Our motivation is mainly originated, but not limited, in explicit MPC application. Recently in [5] it was recognized that the solution to the linear MPC problem with quadratic cost can be formulated as a multi-parametric quadratic program (mp-QP) and solved explicitly, resulting in a piecewise affine (PWA) function of the current state. Similar ideas were developed for linear systems with $1/\infty$ norms in [4], and hybrid and piecewise linear systems in [6]. Also the approximate explicit MPC solution for nonlinear system was treated in [9]. All these approaches lead to a PWA control law defined over a partition of convex polyhedral regions. The evaluation of such a control law requires to determine the polyhedral region which contains the current state, the so-called point location problem. By exploiting the piecewise affinity of the associated value function for MPC with linear cost function, in [1] it was shown that the point location problem can be solved with no need to store the polyhedral partitions provided that a convex PWA function defined over the polyhedral partition is available. In the case of linear cost-function in [11] the point location problem was posed as a weighted Voronoi diagram, which can be solved using an approximate nearest neighbor algorithm. In [7] combining the concept of interval trees and bounding boxes associated with the polyhedral regions, a particular search tree was proposed to solve the point location problem. Although it can be applied to larger partitions, there is no flexibility to trade-off between offline and online complexities in order to guarantee specific requirements. In [21] a Lattice Representation (LR) for the PWA solution of the explicit MPC was obtained, which can save online calculation and memory. Also in [22] a procedure was introduced to trade-off between the warm-start and online computational effort when a combination of explicit MPC and online computation is used. More recently, in [2] exploiting the concept of hashing theory, a two-stage algorithm was proposed which combines the direct search method with an efficient set intersection algorithm together with some extremely efficiently solvable one-dimensional sub-problems (i.e. in the time of order $\mathcal{O}(1)$) to solve the whole problem. The hash-based method enables the designer to trade-off between online and offline complexities while it does not make any assumptions beyond the PWA structure. Therefore it can be applied for a general class of partitions including discontinuous and overlapping ones. Among the existing methods which can be applied (sometimes with some small modifications) to more general class of partitions including discontinuous and overlapping ones, the Binary Search Tree (BST) [19] is acknowledged for its efficient online computational performance. Unfortunately, the offline pre-processing time in this method becomes prohibitive when the complexity of the partition increases. This motivates us to modify the BST method to reduce the pre-processing time and storage requirements by sacrificing online computation time and thereby enabling not only extended applicability of

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this method but also rapid prototyping of embedded control systems where fast design iterations is of vital importance to be able to re-design controllers quickly by taking advantage of extended processing power typical for rapid prototyping hardware. To this aim, by constraining the maximum online computation time, a truncated binary search tree (TBST) is proposed. This truncation leads to extensive reduction in pre-processing time and requires additional search among the pre-computed function pieces remaining at the truncated leaf nodes to locate the optimal region. The BST data structure represents a recursive splitting of the domain of the piecewise function by including a new hyper plane at each node in the search tree. In the BST method these hyper planes are selected among the hyper planes defining the polyhedral regions of the piecewise function. As a reasonable alternative, we propose to select these hyper planes among a carefully selected set of axis-orthogonal hyper planes when constructing the BST. It is discussed in the next section that this replacement leads to faster evaluation of each node when traversing the tree. Furthermore, considering the continuous PWA solution of explicit MPC application an efficient alternative to the required direct search in each truncated leaf is proposed by analytical representation of PWA control law [21] corresponding to each truncated leaf. This representation discards the requirement of storing all polyhedral regions for direct search and thereby reduces the storage complexity to a large extent.

The key features of the proposed method is that the exact solution (to the accuracy of numerical round-off errors) can be computed with pre-defined worst case online computation time guarantees, while pre-processing time and memory use is implicitly minimized subject to this constraint. The computations are readily implementable using fixed-point arithmetic on a low cost microcontroller or DSP since there is no recursive accumulation of round-off errors, and the online algorithm is simple with a small footprint suitable for formal verification of correctness of implementation. This is an advantage compared to other methods that rely on more complex online iterative floating-point computations in numerical optimization solvers [22] and [8], although promising new approaches may remove some of these limitations [17]. Unlike the methods [16],[20],[13],[10] and [15] that benefit from dedicated hardware (such as FPGA and ASIC), the present method targets the typical workhorses of embedded systems - low cost microcontrollers and DSPs, and also rapid prototyping environments. The main contribution of the proposed algorithm is that it allows a flexible tuning and optimization of the trade-off between online and offline complexities. This flexibility provides the user direct control of the use of embedded system resources such as computation time and online memory use, which is essential both in rapid prototyping design and production implementation.

II. PIECEWISE FUNCTION EVALUATION

Definition 1 ([12]): Let a compact set $X \subset R^{n_x}$ be partitioned into a set of N_r convex polyhedral regions $\mathcal{X}_i, i = 1, ..., N_r$ so that $X = \cup_{i=1}^{N_r} \mathcal{X}_i$. A piecewise function $p(x) : X \to R$ is defined as $p(x) = f(x|\phi_i) = f_i(x), \forall x \in \mathcal{X}_i$. Then $p(x)$ is said to be a PWA function if $f_i(x) = [x^T\ 1]\phi_i$, continuous if $f_i(x) = f_j(x), \forall x \in \mathcal{X}_i \cap \mathcal{X}_j$, and non-overlapping if $\mathcal{X}_i \cap \mathcal{X}_j$, $i \neq j$ is not full-dimensional.

A. Explicit MPC Application

Consider a constrained discrete time LTI system:

$$\begin{aligned} x_{t+1} &= Ax_t + Bu_t \\ y_t &= Cx_t \\ x_t &\in \mathbf{X}_c, u_t \in \mathbf{U}_c \end{aligned} \tag{1}$$

Where $A \in R^{n_x \times n_x}, B \in R^{n_x \times m}$ and $C \in R^{p \times n_x}$ and $\mathbf{X_c}, \mathbf{U_c}$ are polyhedral sets containing the origin in their interiors. Then the constrained finite time optimal control (CFTOC) problem for system described in (1) is defined as the following optimization problem:

$$\begin{aligned} J^*(x_t) = \min_U \ & \|Q_f x_{t+N}\|_p + \sum_{k=0}^{N-1} \|Qx_{t+k}\|_p + \|Ru_{t+k}\|_p \\ \textit{subject to} \quad & x_{t+k} \in \mathbf{X}_c \quad \forall\, k = 1, ..., N \\ & u_{t+k} \in \mathbf{U}_c \quad \forall\, k = 0, ..., N-1 \\ & x_{t+k+1} = Ax_{t+k} + Bu_{t+k},\ k \geq 0 \end{aligned} \tag{2}$$

where $U = \left[u_t^T, u_{t+1}^T, ..., u_{t+N-1}^T\right]^T$ is the optimization variable, $\|\cdot\|_p$ denotes the standard vector norm when $p \in \{1, \infty\}$ and for $p = 2$, $\|Qx\|_p = x^T Q x$. As shown in [5] and [4], for $Q \geq 0$ and $R > 0$ the solution to the CFTOC problem (2) at each time t is a time-invariant PWA function of the current state $x(t)$ as:

$$\begin{aligned} u^*(x(t)) &= K_i x(t) + k_i, \quad if\ x(t) \in \mathcal{X}_i \\ \mathcal{X}_i &= \{x \in R^{n_x} | H_i x \leq h_i\}, \forall i = 1, ..., N_r \end{aligned} \tag{3}$$

Therefore, for the state $x(t)$, the online evaluation of explicit MPC requires to find the optimal polyhedral region $\mathcal{X}_i$ containing the state $x(t)$, i.e. $x(t) \in \mathcal{X}_i$.

Remark 1: Note that if $p = 2$ is used, then (3) is a continuous PWA function. For $p = 1/\infty$, if the optimizer is unique, then it is continuous and PWA. Otherwise it is always possible to define a continuous and PWA optimizer $u^*(x)$ for all $x \in \cup_{i=1}^{N_r} \mathcal{X}_i$ [6].

B. Binary Search Tree (BST)

In order to support efficient online evaluation of PWA functions, in [19] a binary search tree is constructed on the basis of the Hyper Planes (HPs) defining the convex polyhedral regions $\mathcal{X}_i$. The idea is to use these HPs as separating variables in the nodes of the tree to split the partitioned space in a way that the number of candidate affine functions decreases as much as possible from the current to the next level of the tree. In online operation, and starting from the root node, one needs to identify on which side of the corresponding HP the current state is located and move through the tree until the optimal region is found. This approach leads to an efficient online evaluation complexity which is logarithmic in the number of regions (N_r) in the best case, with a balanced search tree. When the number of regions increases the cost of construction of the BST increases quickly and becomes

prohibitive for large N_r with the algorithm [19]. This is due to the fact that for constructing such a tree, for each node the BST algorithm in [19] needs to determine on which side of every HP each polyhedral region is located. This requires $2N_rN_H$ linear programs (LPs) to be solved where N_H denotes the number of HPs and is typically much larger than the number of regions. The storage requirement of the BST is in the order of $\mathcal{O}(n_xN_n)$, where N_n denotes the number of nodes of the tree. We emphasis that, less optimal trees can be generated by solving a reduced number of LPs or selecting HPs based on other criteria, see also [24]. This will be presented in section II.C by introducing the idea of combining a truncated binary search tree with direct search, while section II.D introduces the lattice representation as an efficient alternative to direct search.

C. Orthogonal Truncated Binary Search Tree (OTBST)

Consider the set of polyhedral regions $\{\mathcal{X}_1, ..., \mathcal{X}_{N_r}\}$ and the corresponding set of distinct functions $\{f_1, ..., f_K\}$ where $K \leq N_r$, since some regions may share the same function. Let $\{a_j^T x - b_j = 0, j = 1, ..., N_H\}$ denotes the set of all separating HPs defining the polyhedral partition. Let $d_j(x) = a_j^T x - b_j$ and define $\mathcal{J}$ as the index representation of a polyhedron ([19]) which consists of the corresponding HPs determined by d_j and their sign, e.g. $\mathcal{J} = \{2^+, 5^-\}$ means that $d_2(x) \geq 0$ and $d_5(x) \leq 0$. Such a set defines a polyhedron in the state space, i.e. $\mathcal{P}(\mathcal{J}) = \{x | d_2(x) \geq 0,\ d_5(x) \leq 0\}$. Further define the index sets $\mathcal{I}(\mathcal{J}) = \{i | \mathcal{X}_i \cap \mathcal{P}(\mathcal{J}) \text{ is full-dimensional}\}$ and $\mathcal{F}(\mathcal{I}) = \{k |\ f_k \text{ corresponds to } \mathcal{X}_i,\ i \in \mathcal{I}\}$ where $\mathcal{F}(\mathcal{I})$ denotes the index set of all functions corresponding to the index set $\mathcal{I}(\mathcal{J})$. We use the notation $'\pm'$ for statements which should be repeated for both $'+'$ and $'-'$.

Lemma 1 ([19]): If $i \in \mathcal{I}(\mathcal{J}) \cap \mathcal{I}(j^+)$ and $i \notin \mathcal{I}(\mathcal{J} \cup j^+)$, then $\mathcal{X}_i$ is split into two full-dimensional polyhedra by hyper plane j, i.e. $i \in \mathcal{I}(\mathcal{J}) \cap \mathcal{I}(j^+) \cap \mathcal{I}(j^-)$. The same result holds when j^+ is interchanged by j^-.

Lemma 1 provides a computationally efficient approximation of $\mathcal{I}_k^{\pm} = \mathcal{I}(\mathcal{J}_k \cup j^{\pm})$ as $\mathcal{I}(\mathcal{J}_k) \cap \mathcal{I}(j^{\pm})$ when one builds the k-th node of the tree. Based on these definitions and results, we aim to construct a truncated binary search tree to overcome limitations of the BST approach. To this end, let $\mathcal{M}_{clk}$ be the maximum admissible number of clock cycles allocated for online piecewise function evaluation in the processor. We will use $\mathcal{U}$ denoting the list of all indices of those search tree nodes which are currently unexplored. When exploring the k-th node of the tree $\mathcal{N}_k$, let $(\mathcal{I}_k, \mathcal{J}_k)$ be the corresponding index set of regions and hyper planes as already defined. We introduce $\mathcal{C}_k = \mathcal{C}\{\mathcal{I}_k\}$ denoting the maximum number of clock cycles required to find the optimal region through the candidates in the index set $\mathcal{I}_k$ using direct search or other efficient alternatives. Then, one of the following conditions may occur during construction of the tree:

1. $|\mathcal{F}(\mathcal{I}_k)| = 1$, it means the exact solution is obtained and this node is flagged as a leaf node ($\mathcal{L}$).
2. $|\mathcal{F}(\mathcal{I}_k)| > 1,\ \mathcal{C}\{\mathcal{I}_k\} \leq \mathcal{M}_{clk}$ this means the online computational requirement is satisfied and it is possible to directly search through the members of $\mathcal{I}_k$ to find the optimal solution. This node is flagged as a truncated leaf ($\mathcal{TL}$), which is not pursued further in the BST construction.
3. $|\mathcal{F}(\mathcal{I}_k)| > 1,\ \mathcal{C}\{\mathcal{I}_k\} > \mathcal{M}_{clk}$ in this case two child nodes will be added to the tree and pursued further.

These conditions are used to efficiently decide on which level the search tree can be truncated provided that the required online computational performance is guaranteed. Although construction of such truncated binary search tree (TBST) can be done using the same structure and decision criteria as in the BST method (see e.g. [3]), it is possible to achieve much simpler structure of the search tree with considerably less pre-processing time. The main idea is to let the node decision criteria (HPs in BST and TBST methods) to be free (not restricted to the existing HPs). In [23] an optimal selection of decision criteria has been produced by setting up a mixed-integer linear programming problem. Although this can lead to a more efficient solution, but it can be very expensive and still prohibitive in terms of pre-processing time for large partitions. So among all combinations of decision criteria we are interested in orthogonal hyper-planes. We select some candidate OHPs directly based on the information of the existing polyhedral regions. Such a set of candidate OHPs can be obtained by the following simple LPs for each region $\mathcal{X}_r \in X,\ r = 1, ..., N_r$:

$$\min_{x \in \mathcal{X}_r} \pm e_i^T x, \qquad i = 1, ..., n_x \tag{4}$$

where e_i denotes the $i-th$ basic unit vector. The LPs in (4) provide the Bounding Hyper-Rectangle (BHR) representation of each polyhedral region. So $2n_xN_r$ candidate OHPs are produced as a set of candidate discriminating hyper-planes which is extensively less than its counterpart in the BST and also TBST methods. In the next step one can further refine the set of candidate decision variables by removing OHPs. This relies on the fact that the present method allows the binary search tree to end up with a truncated a leaf (which is associated with more than one distinct function) instead of leaf (which is associated with only one function). Considering the orthogonality of OHPs, it is clear that any two parallel OHPs with small distance comparing to the BHR length of the associated polyhedral regions ($< \delta_i$) in the corresponding axis (e_i), are likely not to be informative and removing one of them simplifies the pre-processing stage. A rule of thumb is to keep the one intersecting less regions. For example in Fig.1, $OHP_{6,7}$ are close to $OHP_{1,3}$ respectively and could be removed. In Alg.1 the conceptual steps of building the proposed OTBST are presented.

Algorithm 1: Building the OTBST

Input: Maximum admissible clock cycles $\mathcal{M}_{clk}$ and the minimum distance thresholds $\delta_i,\ \ i = 1, ..., n_x$.

1. Compute the initial set of candidate OHPs using (4) and store the upper and lower bounds of each region as $\mathcal{W}_r = [L_r\ \ U_r],\ r = 1, ..., N_r$. Refine the initial set by removing the redundant OHPs which are identical or closer than δ_i to any parallel OHPs.
2. Let $j \in \bar{J} = \{1, ..., \bar{N}_H\}$ be the set of refined OHPs defined by a pair (i_j, h_j) where $d_j = e_{i_j}^T x - h_j$. Then

compute the index set $\mathcal{I}(j^{\pm})$ for every OHP by a simple comparison based on the available information from step 1, i.e. $\mathcal{W}_r,\ r = 1, ..., N_r$, as

- **IF** $L_r^{i_j} \leq h_j$ **THEN** add r to the index set $\mathcal{I}(j^-)$
- **IF** $U_r^{i_j} \geq h_j$ **THEN** add r to the index set $\mathcal{I}(j^+)$

3. Initialize the root node by setting $\mathcal{N}_1 = \{\mathcal{I}_1, \mathcal{J}_1\} \leftarrow \{(1, ..., N_r), \emptyset\}$ and $\mathcal{U} \leftarrow \{\mathcal{N}_1\}$.
4. **WHILE** $\mathcal{U} \neq \emptyset$ **DO**
   i. Select any $\mathcal{N}_k \in \mathcal{U}$ and set $\mathcal{U} \leftarrow \mathcal{U} \backslash \mathcal{N}_k$.
   ii. For all $j \in J$, compute $\mathcal{I}_k^{\pm} = \mathcal{I}(\mathcal{J}_k) \cap \mathcal{I}(j^{\pm})$ and sort the candidate optimal OHPs by the quantity $\max_{j \in J} \left(\left|\mathcal{F}\left(\mathcal{I}_k^+\right)\right|, \left|\mathcal{F}\left(\mathcal{I}_k^-\right)\right|\right)$ in the ascending order, then collect the index set of all optimal OHPs with minimum quantity, J_k^*.
   iii. Compute the exact solutions $\mathcal{I}_k^{\pm} = \mathcal{I}\left(\mathcal{J}_k \cup j_k^{\pm}\right)$ for all $j_k \in J_k^*$. This is done by solving two LPs $\min_{x \in \mathcal{X}_i} \pm d_{j_k}(x)$ for each $i \in \mathcal{I}(\mathcal{J}_k) \cap \mathcal{I}(j_k^+) \cap \mathcal{I}(j_k^-)$ considering Lemma 1. Choose any optimal solution $j_k = \arg\min_{j_k} \max\left(\left|\mathcal{F}(\mathcal{I}_k^+)\right|, \left|\mathcal{F}(\mathcal{I}_k^-)\right|\right)$, $\mathcal{I}_k^{\pm} = \mathcal{I}\left(\mathcal{J}_k \cup j_k^{\pm}\right)$.
   iv. **IF** $\left|\mathcal{F}(\mathcal{I}_k^{\pm})\right| = 1$ **THEN**
   Flag the resulting new node $\mathcal{N}^{\pm}$ as a leaf node $(\mathcal{L})$, and put $\mathcal{N}^{\pm} \leftarrow \left\{\mathcal{F}(\mathcal{I}_k^{\pm}), 0\right\}$.
   v. **ELSE IF** $\mathcal{C}\left\{\mathcal{I}_k^{\pm}\right\} \leq \mathcal{M}_{clk}$ **THEN**
   Flag node $\mathcal{N}^{\pm}$ as a truncated leaf node $(\mathcal{TL})$, and put $\mathcal{N}^{\pm} \leftarrow \left\{\mathcal{F}(\mathcal{I}_k^{\pm}), -1\right\}$.
   vi. **ELSE**
   Put $\mathcal{N}^{\pm} \leftarrow \left\{\mathcal{I}_k^{\pm}, \mathcal{J}_k \cup j_k^{\pm}\right\}$ as left/right child of the current node and add $\mathcal{N}^{\pm}$ to the list $\mathcal{U}$ as new unexplored nodes.
   vii. **END IF**
5. **END WHILE**

Note that 0 and -1 in steps 4.iv and 4.v denote the leaf and truncated leaf, respectively. The structure of the proposed method in Alg.1 has been illustrated and compared to the BST approach in Fig.1.

Remark 2: Note that based on the approximate criterion in step 4.ii, J_k^* contains indices of all OHPs which minimize the number of possible control laws from the current to the next level of the tree. Then the exact criterion in step 4.iii is applied only to the OHPs which minimize the criterion in step 4.ii.

Remark 3: It is emphasized that the resulting data structure from Alg.1, i.e. $\mathcal{N}$, should be post-processed to build a compact search tree, i.e. $\mathcal{OTBST}$. Unlike the BST method, the proposed OTBST has a fixed node structure independent of problem dimension n_x as shown in Fig.2. Accordingly, the first two numbers in each node, i.e. $\mathcal{OTBST}_k\{1, 2\}$, store the information of optimal OHP, i.e. (i_k, h_k), and $\mathcal{OTBST}_k\{3\ or\ 4\} > 0$ points to the left/right child, while $\mathcal{OTBST}_k\{3\ or\ 4\} < 0$ denotes the leaf node with negative sign of corresponding function index, and $\mathcal{OTBST}_k\{3\ or\ 4\} = 0$ indicates the truncated leaf with the indices of candidate optimal regions stored in $\mathcal{OTBST}_k\{5\ or\ 6\}$.

For a given feasible query point x, the online procedure of piecewise function evaluation is explained in Alg. 2.

Algorithm 2: Online Evaluation Using OTBST
Input: Any feasible query point $x = [x_1, ...x_{n_x}]^T$.

1. Start from the root node $\mathcal{OTBST}_k \leftarrow \mathcal{OTBST}_1$.
2. If $x_{\mathcal{OTBST}_k\{1\}} \leq \mathcal{OTBST}_k\{2\}$, then $r \leftarrow \mathcal{OTBST}_k\{3\}$, else $r \leftarrow \mathcal{OTBST}_k\{4\}$. Return to step 2.
3. If $r > 0$ then $k \leftarrow r$ and go to step 2, else go to step 4 which means the associated child node is a leaf (< 0) or truncated leaf $(= 0)$ node.
4. If $r < 0$ (leaf) then $-\mathcal{OTBST}_k\{3\ or\ 4\}$ denotes the index of the optimal PWA function, respectively, else apply direct search to the set of candidate regions indicated by $\mathcal{OTBST}_k\{5\ or\ 6\}$ to find and evaluate optimal PWA function.

Remark 4: The maximum required number of clock cycles in a truncated leaf node corresponding to the direct search and traversing the tree is typically calculated as $\mathcal{C}_k = \mathcal{C}_k^{ST} + \mathcal{C}_k^{DS} = \mathcal{H}_k^{ST}\mathcal{M}_{OH} + \mathcal{H}_k^{DS}\mathcal{M}_H$, where $\mathcal{H}_k^{ST}$ denotes the number of traversed nodes until the current node, $\mathcal{M}_{OH} = C_{Comp} + 3C_{Mem} + C_{Branch}$ and $\mathcal{M}_H = n_x C_{Mul} + 2C_{Comp} + n_x C_{Sum} + (n_x + 2)C_{Mem} + C_{Branch}$ denote the number of clock cycles required for evaluation of each OHP and HP, respectively, and $\mathcal{H}_k^{DS}$ denotes the number of all HPs corresponding to the candidate regions in node $\mathcal{OTBST}_k$ excluding the region with maximum number of HPs. This is due to the fact that after ordering the $n_{\mathcal{OTBST}_k}$ candidate regions in node $\mathcal{OTBST}_k$ in terms of number of HPs, one needs to check only first $n_{\mathcal{OTBST}_k} - 1$ candidates to find the optimal one. The numbers $(C_{Mul}, C_{Sum}, C_{Comp}, C_{Mem}, C_{Branch})$ represent the number of clock cycles required for performing multiplication, addition, comparison, memory access and branching operations, respectively, on the target processor. In those processors for which some of the operations can be executed concurrently or are combined within a single operation, the formula for $\mathcal{C}_k$ should be modified accordingly.

Remark 5: The optimal OHP j_k from step 4-(iii) may not be unique. Among the set of optimal OHPs which are the same regarding the criterion in step 4-(iii), one can further refine the selection by one of the following secondary criteria:

1. $\min_{j_k}\left(\max\left(\mathcal{C}\{\mathcal{I}_k^-\}, \mathcal{C}\{\mathcal{I}_k^+\}\right)\right)$,
2. $\min_{j_k}\left(\max\left(\left|\mathcal{I}_k^-\right|, \left|\mathcal{I}_k^+\right|\right)\right)$,

Using the first secondary criterion, leads us not only to reduce the number of possible control laws while traversing from one level in the tree to the next, but also the required number of operations in online search and thereby reducing the depth of the truncated tree. The second criterion tries to reduce the number of candidate optimal polyhedral regions from one level of the tree to the next. The analysis of the modified method is similar to the standard BST method except that during the online search in the OTBST method one may end up with a truncated leaf instead of a leaf. In this case it is necessary to search through the possible candidate regions to find the optimal solution.

Remark 6: In the case of explicit MPC applications, usually several regions have the same affine function especially when input constraints are included, so the decision criterion used in Alg.1 often reduces the size of the resulting tree to a

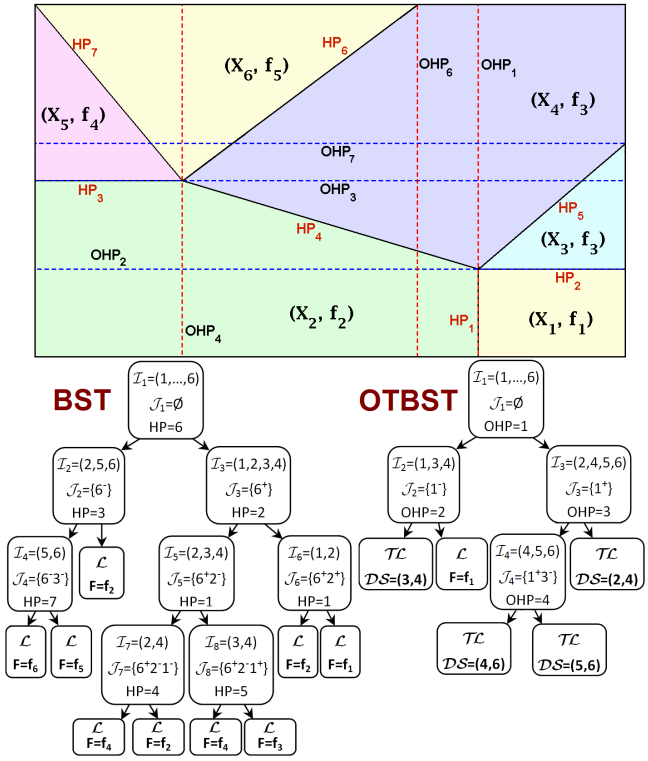

Fig. 1. Illustration of the BST and OTBST methods.

$\mathcal{OTBST}_k\{1,2\}$	$\mathcal{OTBST}_k\{3\}$	$\mathcal{OTBST}_k\{4\}$	$\mathcal{OTBST}_k\{5\}$	$\mathcal{OTBST}_k\{6\}$

Fig. 2. The data structure of each node in the OTBST.

large extent because when all candidate regions in the current node have the same affine function, then it can be considered as a leaf node. Otherwise, when the function pieces are mostly different, it will be more beneficial to replace the criterion in Alg.1 with $j_k = \arg\min_{j_k} \left(\max\left(\mathcal{C}\{\mathcal{I}_k^-\}, \mathcal{C}\{\mathcal{I}_k^+\}\right)\right)$ as described in the Remark 5.

The main features of the proposed OTBST method can be summarized as follows. (i) The total number of discriminating OHPs is usually much less than the HPs in the BST method, leading to a significant reduction in the pre-processing time, (ii) In the first step of building the search tree one has to determine for each node decision criteria (OHP), which side every region $\mathcal{X}_r$ lies on. This requires $2N_H N_r$ linear programs which can be replaced by simple comparison when OHPs are used (see Alg.1, step 2), giving further reduction in the pre-processing demands, (iii) Unlike the BST method, the OTBST approach enables the designer to trade-off between offline and online complexities, and (iv) In the OTBST the online evaluation of each node is more efficient than the BST. Traversing each node in the OTBST requires a single comparison, 3 memory accesses and 1 branching operations, while it takes n_x multiplications, n_x additions, 1 comparison, n_x+2 memory accesses and 1 branching operation in the BST approach.

Remark 7: The last property (iv) implies that traversing each node of the tree in the OTBST is computationally more efficient than the BST, especially when multiplication requires several clock cycles in a simple embedded (micro) controller. However, the major part of the online evaluation time in the OTBST method usually belongs to the direct search through the candidate regions recognized by truncated leaves and can be dominant comparing to the online evaluation time of the BST method. To deal with this problem, in the next section considering continuous PWA solution of explicit MPC an alternative is proposed by representing each truncated leaf in a compact analytical form that usually provides faster evaluation and less memory requirements than direct search used approach.

D. Lattice Representation of Truncated Leaves

In this section, assuming continuous and non-overlapping PWA function evaluation we introduce an efficient approach as an alternative to the direct search in section II.C. To this aim we use the modified form of lattice representation model [21] to represent each PWA function associated with each truncated leaf.

1) Modified Lattice Representation (LR): The Lattice representation model has a universal representation capability and describes a PWA function in terms of its local affine functions and the order of the values of all the affine functions in each region [21],[18].

Lemma 2 ([18]): Given any n-dimensional continuous PWA function $p(x)$, there is a lattice PWA function $P(x|\Phi,\Psi)$ such that $p(x) = P(x|\Phi,\Psi)$ holds for all $x \in R^n$ and

$$P(x|\Phi,\Psi) = \min_{1\le i\le N_r} \left\{ \max_{\substack{1\le j\le N_r \\ \psi_{ij}=1}} \{f(x|\phi_j)\} \right\} \tag{5}$$

where $\Phi = [\phi_1, ..., \phi_{N_r}]^T$, $\Psi = [\psi_{ij}]$ and

$$\psi_{ij} = \begin{cases} 1 & if \;\; f_i(x) \ge f_j(x) \\ 0 & else \end{cases} \tag{6}$$

As shown in [21] any continuous PWA function can be fully specified by a parameter matrix Φ and structure matrix Ψ.

Remark 8: As noted in Remark 1 the multi-parametric solver may return a PWA solution that is not necessarily continuous if $p = 1/\infty$ although a continuous solution always exists. Then the lattice representation algorithm is feasible for the continuous PWA solutions obtained from the multi-parametric solver.

Using the properties of min-max representation form of the lattice model and the possibility of having several regions with the same affine function, two simplification algorithms were proposed in [21], i.e. row and column vector simplification lemmas. The row vector simplification algorithm is presented in Lemma 3. It is emphasized that the column vector simplification lemma in [21] may lead to misrepresentation for some PWA functions (see Appendix-A for a counterexample). To prevent misrepresentation the column vector simplification lemma has been modified in this paper. The modified lemma is presented in Lemma 4.

Lemma 3 (Row Vector Simplification Lemma [21]): Assume that $P(x|\ \Phi, \Psi)$ is a lattice representation with N_r segments. Let ψ_i, ψ_j be rows of the structure matrix. If the pointwise inequality $\psi_i - \psi_j \leq 0$ holds for any $i, j \in 1, ..., N_r$, there exists a simplified structure matrix $\tilde{\Psi} \in R^{(N_r-1)\times N_r}$, such that $P(x|\Phi, \Psi) = P(x|\Phi, \tilde{\Psi})$, where $\tilde{\Psi} = [\psi_1^T, ..., \psi_{j-1}^T, \psi_{j+1}^T, ..., \psi_{N_r}^T]^T$.

Lemma 4 (Column Vector Simplification): Assume that $P(x|\ \Phi, \Psi)$ is a lattice representation with N_r segments. Let $\Psi = [\psi_{ij}]^{N_r\times N_r}$ and $\hat{\Psi} = [\hat{\psi}_{ij}]^{N_r\times N_r}$ denote the primary and dual structure matrices and define $I_i = \{k|f_k(x) \leq f_i(x), \forall x \in \mathcal{X}_i\}$. Then the following results hold.

(i). Given any $i, j, k \in \{1, ..., N_r\}$, if $k, j \in I_i$ and $\hat{\psi}_{jk} = 1$, then set $\psi_{ij} = 0$ and $\hat{\psi}_{kl} = 0,\ \forall l = 1, ..., N_r$.

(ii). if $\psi_{ij} = 0, \forall i \in \{1, ..., N_r\}$, then there exist a simplified structure matrix $\tilde{\Psi} \in R^{(N_r-1)\times N_r}$ and parameter matrix $\tilde{\Phi} \in R^{N_r\times(N_r-1)}$ such that $P(x|\Phi, \Psi) = P(x|\tilde{\Phi}, \tilde{\Psi})$, where $\tilde{\Phi} = [\phi_1, ..., \phi_{j-1}, \phi_{j+1}, ..., \phi_{N_r}]^T$ and $\tilde{\Psi}$ is the same as defined in Lemma 2.

Proof: The proof is the same lines as the proof in [21] except that the Eq. 20 in [21] is now hold for all cases considering the extra condition in Lemma 4-(i). ■

Utilizing the compact analytical model in (5)-(6) we aim to combine the OTBST and lattice representation approaches in a unified structure enjoying the advantages of both approaches. We emphasize that the OTBST method benefits from very low preprocessing time comparing to the BST method while the lattice representation approach provides a compact representation for the PWA function comparing to the polyhedral representation which is required in the OTBST for direct search. As a result, it can reduce the storage requirement to a large extent. Furthermore, since in online applications traversing the OTBST is done in logarithmic time, thus replacing the direct search with the corresponding LR model can also reduce the online computation time taking the advantages of the simplification lemmas into account. The approach of lattice-based OTBST (LOTBST) is described in Alg.3. We remark, in the proposed approach the only information which is required to be stored for direct search in online application is structure and parameter matrices associated with each orthogonal truncated leaf instead of storing all polyhedral regions.

Algorithm 3: Lattice-OTBST (LOTBST)

Offline Procedure

1. Calculate the explicit MPC solution.
2. Calculate $\mathcal{OTBST}$ by applying Alg.1 to the PWA control law obtained in step 1.
3. Using the Lemma 2 calculate lattice representation (parameter and structure matrices) associated with each truncated leaf ($\mathcal{TL}$) in the $\mathcal{OTBST}$.
4. Simplify the lattice representation using Lemmas 3 and 4.

Online Procedure

1. For a given query point $x \in X$ apply Alg.2 to locate a leaf or truncated leaf node where x is located.
2. If x belongs to a leaf node, then evaluate the corresponding affine function, else use (5) to obtain $p(x)$.

Remark 9: Considering Remark 4, the maximum required number of clock cycles to evaluate an orthogonal truncated leaf node in LOTBST approach must be calculated. Let N_k denotes the number of candidate regions in node $\mathcal{OTBST}_k$. Then, the online evaluation of LR model corresponding to each orthogonal truncated node consists of three parts. At first N_k affine functions should be evaluated. In the worst case, this requires $n_x N_k$ multiplications and $n_x N_k$ sums. Then one need to calculate $N_k(N_k - 1)$ maximization terms and $N_k - 1$ minimization terms to evaluate LR model, in the worst case. Therefore, this min-max calculation requires $N_k^2 - 1$ comparisons totally. Finally, the LR model evaluation requires to access structure and parameter matrices which consist of $N_k^2 + N_k(n_x + 1)$ data. Therefore, $\mathcal{C}_k^{DS}$ is replaced with $\mathcal{C}_k^{LR} = (n_x N_k)C_{Mul} + (n_x N_k)C_{Sum} + (N_k^2 - 1)C_{Comp} + (N_k^2 + N_k(n_x + 1))C_{Mem}$, denoting the maximum required number of clock cycles corresponding to the lattice model evaluation of the current node. We emphasize that the actual required clock cycles for LR evaluation may be reduced applying Lemmas 3 and 4.

Remark 10: Note that the structure matrix contains only 0/1 elements, and therefore it is possible to pack and store these elements as bits of an integer number in the form of byte or word. This reduces the storage complexity as well as online calculation corresponding to reloading structure matrix. However it requires some online computation to decode 0/1s from integer values. This provides further flexibility to trade-off between storage and online computational complexities.

Remark 11: We emphasize that in the pure LR approach the storage requirement depends on the size of structure and parameter matrices. On the other hand, when the number of regions increases, the storage complexity may increase quickly in the worst case where the simplification lemmas have no major effect, e.g. where most of the affine function pieces are different. Hence, another important advantage of combining truncated search tree and LR model in the proposed approach is referred to this fact that each truncated node contains a much smaller number of regions and it is more likely that some of those regions have the same affine function for which the simplification lemmas lead to a significant simplification. Furthermore, it is evident from the above explanation that one can easily trade-off between the computation (online/offline) and storage complexities by truncating the tree at different levels. To this aim, the parameter $\mathcal{M}_{clk}$ is a tuning knob which can control not only the mentioned trade-off but also guaranies the prerequisite online computation time according to the hardware on hand. This feature is demonstrated by several numerical examples in section III (See Tables I and II for more details).

III. EXAMPLES

In this section the proposed piecewise function evaluation methods (OTBST and LOTBST), binary search method (BST), and pure lattice representation method (LR) have been implemented and compared via several examples. The clock cycle specifications in the following simulations are chosen based on the typical embedded (micro) controllers where multiplication, addition, comparison, memory access and branching

operations take $(2, 1, 1, 2, 2)$ clock cycle(s) to be carried out, respectively.

Example 1: Double Integrator
Consider the discrete-time version of the double integrator

$$x(t+1) = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix} x(t) + \begin{bmatrix} T_s^2 \\ T_s \end{bmatrix} u(t) \qquad (7)$$

where $T_s = 0.05s$ and the system is subject to input constraints, $|u(t)| \leq 1$, and output constraint $|y(t) = x_2| \leq 1$. The CFTOC problem (2) is solved with $p = 2, Q = diag([1, 0]), R = 1, Q_f = 0_{2\times 2}$ for different horizon values $N = 2, 4, 8, 12$ and 35. The explicit solutions characteristics and the comparison results of applying different PWA function evaluation methods are presented in Table I. The corresponding number of distinct PWA functions are $25, 133, 337, 609$ and 655, respectively. The pre-processing time in the OTBST and LOTBST methods have been extensively reduced comparing to the BST method with moderate extra online computation time. However the number of required online clock cycles is guaranteed to be admissible while constructing the tree in all approaches using the parameter $\mathcal{M}_{clk}$. The off-line computations were done on a 3GHz Pentium IV computer with some aid of the MPT toolbox for Matlab [14]. Considering the third test case $(N = 8)$, in Fig.3 it is shown that the proposed LOTBST method efficiently parameterizes alternative solutions with online computational performance between the pure LR and BST approaches when the parameter $\mathcal{M}_{clk}$ decreases from its upper to lower value limited by the LR and BST methods. Note that even for small $\mathcal{M}_{clk}$, in the OTBST and LOTBST approaches, most often there are some regions to be directly searched or represented by LR model. That is why it is not possible to exactly achieve the BST performance. This fact can be seen in Fig.3 as a discontinuity. For the same test case $(N = 8)$ and using a low cost processor, e.g. AVR-XMEGA series, with 32 MHz clock frequency, the PWA function evaluation procedure in the BST, OTBST and LOTBST methods, loads the processor with about 0.02%, 0.07% and 0.07%, respectively, when the sampling time $T_s = 0.05s$ is considered. In this case the direct search approach loads the processor with about 5%. Furthermore, the results in all test cases demonstrate extensive reduction in storage requirements when LOTBST is applied.

Example 2: Ball & Plate
This example deals with the so-called Ball & Plate system of [6] in the form of regulating to the origin. The explicit controller was obtained using the MPT toolbox for MATLAB resulting in 2024 regions in 4 dimensions with 493 distinct PWA functions (see Appendix-B for model information). The comparison results of applying different methods to this example are presented in Table II for $\mathcal{M}_{clk} = 51 \times 10^3$. Note that, using the low cost micro-controller in the previous example, the PWA function evaluation at sampling time $T_s = 0.03sec$ loads the processor with about 4.9% in the OTBST approach, while it takes about 0.06% and 2.6% when the BST and LOTBST methods are used. Note that the BST approach requires more than 95 hours preprocessing time while the proposed LOTBST takes about 40 minutes and achieves the online performance two times better than the required $\mathcal{M}_{clk}$. For this example the DS method takes 43% of the processor time in each sampling interval. As it was expected before and can be seen from the results in Table II, when the problem dimension and consequently the complexity of the resulting search tree increase, then the number of nodes explodes quickly in the lower levels of the tree. Therefore truncating the tree can moderate the growth of nodes or storage requirement as shown in Table II. According to the results, the OTBST and LOTBST approaches reduce the storage requirement with about 35% and 97%, respectively comparing to the BST approach. Another advantage of the proposed methods is their significantly lower pre-processing time comparing to the BST method. For example in the OTBST and LOTBST methods the pre-processing time has been reduced by orders of magnitude whereas the online computation time still satisfies the problem requirements declared by $\mathcal{M}_{clk}$. Finally, it is worthwhile to emphasize that more than 90% of the required memory in the OTBST approach is owned by the storing the polyhedral regions for direct search which is discarded in the LOTBST method and leads to about 97% reduction in the storage requirement comparing to the BST, and also the online computation time has been reduced about 43% comparing to the OTBST approach.

TABLE I
THE COMPARISON RESULTS OF EXAMPLE 1 FOR DIFFERENT HORIZON. — DENOTES IT IS NOT APPLIED TO THIS METHOD, AND * DENOTES THE ALGORITHM IS NOT TRACTABLE DUE TO THE HIGH PRE-PROCESSING TIME.

N	Method	N_r	$\mathcal{M}_{clk}$	N_n	Storage (Numbers)	Preprocessing Time(sec)	Online Clock-Cycles Min	Online Clock-Cycles Max
2	BST	83	—	188	752	27	147	187
	OTBST		550	33	1160	3	62	454
	LOTBST				179	5	136	323
	LR		—	—	256	0.2	16625	
4	BST	219	—	421	1792	160	147	207
	OTBST		1000	39	2890	6	73	952
	LOTBST				307	11	165	861
	LR		—	—	665	1	54711	
8	BST	627	—	1177	4736	1321	187	247
	OTBST		1250	90	8230	40	62	1165
	LOTBST				716	51	95	1174
	LR		—	—	2585	4	317585	
12	BST	1325	—	2181	8704	5769	207	267
	OTBST		1700	131	17095	118	73	1531
	LOTBST				1177	151	95	1696
	LR		—	—	7756	19	1158990	
35	BST	7333	—	*	*	*	*	*
	OTBST		3800	236	89700	1725	62	2945
	LOTBST				1382	1780	84	3742
	LR		—	—	8960	354	1315857	

IV. CONCLUSIONS

The problem of evaluating piecewise functions defined over polyhedral regions was investigated motivated by its application in the embedded control systems. To this aim the well known BST approach was modified. At first a truncated tree was introduced, then an orthogonal truncated tree was established by introducing artificial orthogonal dis-

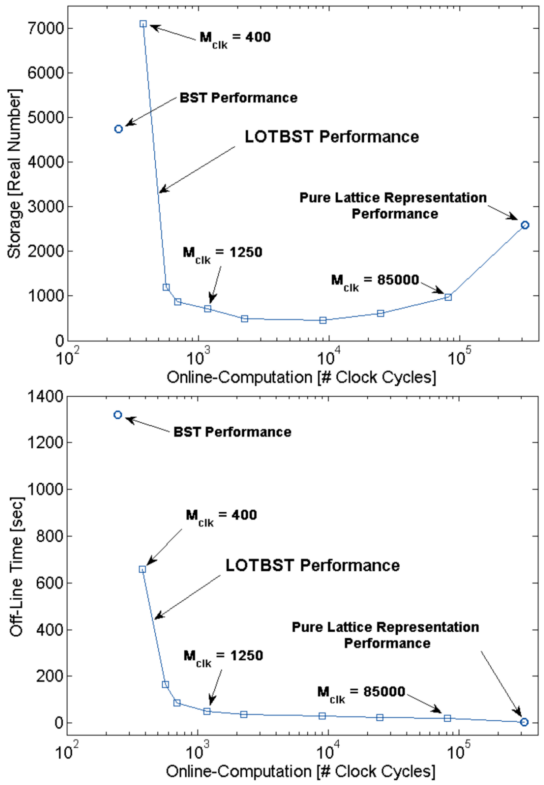

Fig. 3. Trade-off characteristics of the proposed LOTBST method, parameterizing performance of the BST and pure LR approaches.

TABLE II
THE COMPARISON RESULTS OF EXAMPLE 1 FOR DIFFERENT HORIZON. — DENOTES IT IS NOT APPLIED TO THIS METHOD.

Method	N_r	$\mathcal{M}_{clk}$	N_n	Storage (Numbers)	Preprocessing Time(sec)	Online Clock-Cycles Min	Online Clock-Cycles Max
BST	2024	—	23514	141084	343297	373	613
OTBST		51×10^3	69	91196	724	68	47370
LOTBST				4556	2410	2067	24722
LR		—	—	8985	60	1684594	

criminating hyper-planes instead of the HPs resulting from the polyhedral region descriptions giving extensive reduction in the preprocessing time comparing to the BST. Furthermore, as an important application the explicit MPC problem was considered which requires a continuous PWA function to be evaluated online. In the case of continuous PWA functions, as an alternative to the required direct search in the OTBST we proposed the LOTBST approach which represents control hyper-surfaces in each orthogonal truncated leaf in a compact analytical form utilizing the lattice representation model. According to the simulation results, the LOTBST approach is able to improve both online computation time and storage requirement of pure LR approach. Also, it reduces extensively the storage complexity and offline computation time in the BST approach, while guaranteeing the required online computation time. In summary, the simulation results showed that the proposed approaches open up the flexible use of binary search trees to a wider class of problems for which neither the BST nor LR approaches can be applied because of either prohibitive preprocessing time and storage requirement or high online computational complexity, respectively. We emphasize that, although the LOTBST method usually outperforms the proposed direct search based approach, i.e. OTBST, but it should be emphasized that the OTBST is a global approach that can be applied to general piecewise nonlinear (PWNL) functions including discontinuous and overlapping.

APPENDIX A

Repeated use of the column vector simplification lemma of [21] may lead to misrepresentation in some cases. To resolve this problem an extra condition $\hat{\psi}_{kl} = 0$, $\forall l$ was added in Lemma 4-(i). This problem is originated in this fact that the lemma in [21] has been analyzed and proved for one iteration of simplification for which a piece of PWA function f_i is removed since it can be represented by another piece f_j in its min-max form. When the lemma is used iteratively, the problem arises if the function piece f_j is itself removed by another representative f_k which is not a representative for f_i. This problem is illustrated in the following example.

$$\mathrm{p}(x) = \begin{cases} f_1 = -x-3 & \forall x \in \mathcal{X}_1 = [-6 \ \ -4] \\ f_2 = 1 & \forall x \in \mathcal{X}_2 = [-4 \ \ -2] \\ f_3 = x+3 & \forall x \in \mathcal{X}_3 = [-2 \ 0] \\ f_4 = -x+3 & \forall x \in \mathcal{X}_4 = [0 \ 2] \\ f_5 = 1 & \forall x \in \mathcal{X}_5 = [2 \ 4] \end{cases} \tag{8}$$

The parameter and structure matrices are calculated as

$$\Psi = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 \end{bmatrix}, \quad \Phi = \begin{bmatrix} -1 & -3 \\ 0 & 1 \\ 1 & 3 \\ -1 & 3 \\ 0 & 1 \end{bmatrix} \tag{9}$$

The simplified matrices are obtained as

$$\tilde{\Psi} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \end{bmatrix}, \quad \tilde{\Phi} = \begin{bmatrix} -1 & -3 \\ 1 & 3 \\ -1 & 3 \\ 0 & 1 \end{bmatrix} \begin{matrix} \rightarrow f_1 \\ \rightarrow f_3 \\ \rightarrow f_4 \\ \rightarrow f_5 \end{matrix} \tag{10}$$

It is easy to verify that the resulting lattice representation does not match the original PWA function for $x \in \mathcal{X}_2$.

APPENDIX B

The dynamical model for the y-axis of Ball & Plate system is given by

$$\dot{x}(t) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 700 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & -34.7 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 3.1 \end{bmatrix} u(t) \tag{11}$$

where $x := [y, \dot{y}, \alpha, \dot{\alpha}]^T$ is the state vector, $|y| \leq 30$, $|\dot{y}| \leq 15$, $|\alpha| \leq 0.26$ and $|\dot{\alpha}| \leq 1$ are the state constraints and $|u| \leq 10$ denotes the input constraint. The model (11) was then discretized with $T_s = 0.03sec$. The following parameters $N = 10$, $Q = diag([6, 0.1, 500, 100])$, $R = 1$ and $P = Q$ were considered in Example-2.

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