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To cite this version:
Parisa Ahmadi-Moshkenani, Tor Johansen, Sorin Olaru. Combinatorial Approach towards Multi-Parametric Quadratic Programming based on Characterizing Adjacent Critical Regions. IEEE Transactions on Automatic Control, Institute of Electrical and Electronics Engineers, In press, pp.1. 10.1109/TAC.2018.2791479 : hal-01720260

HAL Id: hal-01720260
https://hal-centralesupelec.archives-ouvertes.fr/hal-01720260

Submitted on 1 Mar 2018

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Combinatorial Approach towards Multi-Parametric Quadratic Programming based on Characterizing Adjacent Critical Regions

Parisa Ahmadi-Moshkenani, Tor Arne Johansen, and Sorin Olaru

Abstract—Several optimization-based control design techniques can be cast in the form of parametric optimization problems. The multi-parametric quadratic programming (mpQP) represents a popular class often related to the control of constrained linear systems. The complete solution to mpQP takes the form of explicit feedback functions with a piecewise affine structure, valid in polyhedral partitions of the feasible parameter space known as critical regions. The recently proposed combinatorial approach for solving mpQP has shown better efficiency than geometric approaches in finding the complete solution to problems with high dimensions of the parameter vectors. The drawback of this method, on the other hand, is that it tends to become very slow as the number of constraints increases in the problem. This paper presents an alternative method for enumerating all optimal active sets in a mpQP based on theoretical properties of adjacent critical regions and their corresponding optimal active sets. Consequently, it results in excluding a noticeable number of feasible but not optimal candidate active sets thereby increasing the efficiency of the algorithm. Therefore, the number of linear programs that should be solved decreases noticeably and the algorithm becomes faster. Simulation results confirm the reliability of the suggested method in finding the complete solution to the mpQPs while decreasing the computational time compared favourably with the best alternative approaches.

I. INTRODUCTION

Exploiting multi-parametric quadratic programming (mpQP) for solving model predictive control (MPC) problems enables the online computational burden of the problem to be moved offline [1], [2] and [3]. Consequently, application of MPC can be extended to systems with relatively fast dynamics. In a mpQP problem, the Karush-Kuhn-Tucker (KKT) optimality conditions can be used to characterize the affine local parametric optimal solution for every fixed combination of optimal active constraints as well as the representation of the polyhedral critical region (CR) which is the domain of validity of affine optimal solution for that optimal active set. There are basically two approaches towards solving a mpQP problem. i) Geometric approaches that iteratively build a partition of parameter space using geometric (polyhedral) computations [4]–[9] ii) combinatorial approaches which are based on implicitly enumerating all possible combinations of active constraints in a combinatorial search tree [10]–[12]. The advantage of geometric approaches is that mostly optimal combinations of active sets are considered, avoiding unnecessary computations due to the combinatorial number of possible active sets. However, for problems of high dimension of the parameter space, geometric computations become numerically sensitive and these algorithms, therefore, tend to become slow and unreliable. This is due to the fact that high-dimensional geometric problems (such as computing the centers of lower-dimensional facets) cannot be solved reliably even with state-of-the-art solvers [13]. Combinatorial approaches, on the other hand, avoid geometric computations and hence deal quite effectively and efficiently with mpQP problems having a higher number of parameters where the geometric methods perform poorly and may fail finding the complete solution [13]. Furthermore, the enumerative feature of these methods makes them suitable for region-free explicit model predictive controls suggested by [14] and [15] where creating the critical regions, which is computationally demanding in high dimensional parameter spaces, is not required. Another enumeration-based method for solving linear and semi-definite quadratic multi-parametric programs is recently proposed in [13] based on reformulating these problems into parametric linear complementarity problems (PLCP). This method has shown to be, in the best case reported in [13], twice as fast as method of [10]. The pruning criterion in all these enumerative methods is to simultaneously cut off branches with infeasible active sets which is crucial for achieving optimal efficiency in enumeration. A drawback of these methods, however, is that the number of possible combinations of active constraints increases exponentially with the number of constraints. Therefore, their applications are limited to problems with few constraints [12]. Very recently [16] has introduced a connected-graph approach towards solving mpQPs which bridges the division between geometrical and combinatorial approaches. Similarly to the method suggested by [5], identifying the type of each facet of a full-dimensional CR, i.e. investigating which constraint becomes active or inactive on that facet, is required during the offline procedure in order to find adjacent CRs which can result in the same drawbacks as geometric approaches when dealing with mpQPs with large number of parameters. Moreover, when two or more lower-dimensional critical regions overlap along a facet of a full-dimensional critical
region due to violation of strict complementarity slackness condition, characterising that facet as one of the intended types is not possible. This paper suggests an alternative combinatorial approach towards solving mpQPs which avoids geometric computations completely, resulting in faster and more reliable computation of solution for high number of parameters compared to other approaches. The objective of this method is to exclude a noticeable number of feasible active sets that are not optimal from the combinatorial tree in order to accelerate the enumeration of all optimal sets. To this aim, [17] has suggested a downward and upward exploration of combinatorial tree which exploits the underlying relationship between two full-dimensional adjacent critical regions when degeneracy does not occur on their common facet. This method is guaranteed to find all critical regions in non-degenerate cases while reducing the number of LPs that should be solved. Hence the required computational time decreases significantly. A modification to the method in [17] is presented in [18] to handle degeneracies based on theoretical properties of full-dimensional adjacent critical regions for which degeneracy occurs on their common facet and the relation between their corresponding optimal sets. This method enables enumeration of all optimal active sets in a general case which can be subject to degeneracies as well. This paper completes this trend of development by presenting the complete theoretical framework exploited in combinatorial approach and offers additional discussions, numerical studies, comparisons and examples.

The first part of the this paper presents the combinatorial approach towards mpQP in conjunction with the suggested downward and upward exploration of the combinatorial tree. The algorithm for exploring the combinatorial tree is presented in section III along with a series of theorems describing the theoretical foundation. Simulation results are presented in section IV. Moreover, the comparison between different methods for solving mpQP problems, implemented in Multi-Parametric Toolbox [9], is presented which confirms the superiority of the suggested method w.r.t. other approaches for problems with a large number of constraints, and finally the paper is concluded in section V.

II. COMBINATORIAL APPROACH TOWARDS MULTI-PARAMETRIC QUADRATIC PROGRAMMING

Consider the following multi-parametric quadratic program:

\[
V^*_N(x) = \min_{z} \frac{1}{2} z^T H z
\]

\[\text{s.t. } G z \leq S x + W\]

which is an equivalent to the standard multi-parametric quadratic program including quadratic, linear and constant terms in the cost function and is derived by applying appropriate transformation. See for example [1]. Here \(z \in \mathbb{R}^n\) and \(x \in \mathbb{R}^n\) denote the vectors of optimization variables and parameters, respectively. Assume that the problem is strictly convex, i.e. \(H > 0\). As shown by [1], the Karush-Kuhn-Tucker (KKT) optimality conditions can be used to characterize the analytic solutions to the mpQP problem:

\[
\begin{align*}
Hz + G^T \lambda &= 0, \\
\lambda (G^i z - W^i - S^i x) &= 0, & i = 1, \ldots, q, \\
\lambda &\geq 0, & G z \leq S x + W
\end{align*}
\]

Defining \(Q = \{1, \ldots, q\}\) as the index set of all constraints in (1b), we recall that a constraint among \(q\) constraints in (1b) is said to be active if it holds with equality for a given \(z\) and \(x\), and inactive if it holds with strict inequality. Thus the active set \(A(z, x)\) can be described as \(A(z, x) := \{i \in Q \mid G^i z - S^i x - W^i = 0\}\) while the corresponding inactive set \(J(z, x)\) is given by the set difference of \(Q\) and \(A\) i.e. \(J(z, x) := Q \setminus A(z, x)\). Denoting \(A\) and \(J\) as the active and inactive sets, one can rewrite the KKT conditions as follows:

\[
\begin{align*}
H z + G^A^T \lambda^A &= 0, \\
G^A z - W^A - S^A x &= 0, \\
G^J z - W^J - S^J x &\leq 0, \\
\lambda^A &\geq 0, & \lambda^J &= 0
\end{align*}
\]

Before going further, we recall some definitions and theorems.

**Definition 1.** Redundant constraints: Let a polyhedron \(\Theta\) be represented by \(A \theta \leq b\). We say that \(A^i \theta \leq b^i\) is redundant if \(A^i \theta \leq b^i, \forall j \neq i \Rightarrow A^i \theta \leq b^i\) (i.e., it can be removed from the description of the polyhedron).

**Definition 2.** Minimal representation: A representation of a polyhedron is minimal if there are no redundant constraints.

**Assumption 1.** The constraints in (1) are assumed, without loss of generality, to form a minimal representation of the polyhedral feasible set.

**Definition 3.** Linear Independence Constraints Qualification (LICQ), (Nocedal and Wright, 1999): Given \(z^*(x), \lambda^*(x)\) satisfies the KKT conditions. LCS holds if exactly one of \(\lambda^*(x)\) and \(G^i z^*(x) - S^i x - W^i\) is zero for each \(i \in Q\), i.e., \(\lambda^*(x) > 0\) for each \(i \in A(z^*(x), x)\) and \(s^i > 0\) for each \(i \in J(z^*(x), x)\) where \(s^i\) is the slack variable of inactive constraint \(i \in J\) such that \(G^i z^*(x) + s^i = S^i x + W^i\). For a constraint that is assumed to be active, if (3) is feasible with the associated Lagrange multiplier \(\lambda^i\) equal to zero, we define that constraint as weakly active constraint. On the other hand, if (3c) holds with strict equality for a constraint that is assumed to be inactive, we call that constraint as weakly inactive constraint. Furthermore, an optimization problem for which both the LICQ condition and the SCS condition hold is known to be non-degenerate according to the definition of degeneracy in [5].

**Definition 4.** Full-dimensional polyhedron: Let \(X\) be a polyhedron in \(\mathbb{R}^n\). If the dimension of the affine hull of \(X\),
defined as the set of affine combinations of points in \( X \), is equal to \( n \), then \( X \) is full-dimensional.

**Theorem 1:**

Consider the problem in (1) with \( H > 0 \). Let \( X \subseteq \mathbb{R}^n \) be the problem’s polyhedral feasible set and let \( x \in X \). Then the solution \( z^*(x) \) and the Lagrange multipliers \( \lambda^*(x) \) of a mpQP are piecewise affine functions of the parameter \( x \) and \( z^*(x) \) is continuous. Moreover, if LICQ holds for all \( x \in X \), \( \lambda^*(x) \) is also continuous.

**Proof:** See [1]

Assuming that we know an optimal active set \( A \) and that LICQ holds, we can use (2a) and (2b) to derive the parameter-dependent optimizer [1]:

\[
z_A(x) = H^{-1}(G^A)^T H^{-1}_{GA}(W^A + S^A x)
\]

(4)

where the existence of \( H^{-1}_{GA} := (G^A H^{-1} (G^A)^T)^{-1} \) is guaranteed due to the LICQ and positive definiteness of \( H \). The set of inequalities in (2c) characterize the so-called critical region (CR) for the considered optimal active set \( A \). The CR is in the form of a polyhedron in the parameter space defined by the following inequalities:

\[
H^{-1}_{GA}(W^A + S^A x) \leq 0
\]

(5a)

\[
GH^{-1}(G^A)^T H^{-1}_{GA}(W^A + S^A x) \leq W + S x
\]

(5b)

This polyhedron is the largest set of parameters \( x \in X \) for which the combination of active constraints \( A \) at the optimizer remains unchanged and hence, the optimizer is given by (4).

To enumerate all optimal active sets, [10] suggests to choose the candidate active sets from the power set of \( Q \) in the order of increasing cardinality. It should be noted that for a QP with \( m \) decision variables and \( q \) constraints, only a maximum of \( m = \min(m, q) \) linearly independent constraints can be strongly active at the optimal solution [19]. For each candidate active set, \( A_i \), the following LP should be solved to check whether it can be optimal or not:

\[
\begin{align*}
\max & \quad t \\
\text{s.t.} & \quad t e_1 \leq \lambda^{A_i}, t e_2 \leq s^{J_i} \\
& \quad t \geq 0, \lambda^{A_i} \geq 0, s^{J_i} \geq 0 \\
& \quad H z + (G^A)^T \lambda^{A_i} = 0 \\
& \quad G^{A_i} z - S^{A_i} x - W^{J_i} = 0 \\
& \quad G^{J_i} z - S^{J_i} x - W^{A_i} + s^{J_i} = 0
\end{align*}
\]

(6)

Here \( t \) is a scalar optimization variable and \( e_1 = [1, \ldots, 1]^T \) and \( e_2 = [1, \ldots, 1]^T \) are vectors of appropriate sizes corresponding to the vector of Lagrangian multipliers \( \lambda^{A_i} \) and the vector of slack variables \( s^{J_i} \), respectively. Inequalities (6b) form an upper bound on the optimization variable \( t \) as the minimal value contained in \( \lambda^{A_i} \) and \( s^{J_i} \). This formulation allows the immediate identification of failure of the SCS condition whenever \( t = 0 \). Note that, according to the formulation in (6), we adopt the freedom to split the set of constraints in Active and Inactive while both are capable of violating the SCS condition through a zero Lagrange multiplier or a zero slack variable, respectively. However, since the objective in (6) is optimized over the parameter space \( x \) as well, (6) does not yield a zero Lagrange multiplier or a zero slack variable unless it is zero over the entire critical region corresponding to \( A_i \) whether it is full-dimensional or lower-dimensional. Hence, the situations where both \( \lambda_i = 0 \) and \( G^{A_i} z - S^{A_i} x - W^{J_i} = 0 \) hold for constraint \( i \) on the boundaries of a full-dimensional critical region are not considered as violation of SCS condition. If the candidate active set is found not to be optimal, i.e., if the optimization problem in (6) is not feasible, another optimization problem should be solved by removing all constraints arising from the optimality condition (namely all constraints including \( \lambda^{A_i} \) in (6)), to check for the feasibility of the candidate active set. If this optimization problem is not feasible, we can exclude \( A_i \) and all its supersets from the combinatorial tree. This is the only pruning criterion in this method which is based on the infeasibility of a combination of active constraints. A graphical illustration of the combinatorial enumeration strategy and the involved pruning process is given in the form of a combinatorial tree diagram in Fig. 1. As it can be seen from Fig. 1, all feasible combinations of active constraints remain in the combinatorial tree for exploring the levels below while for many cases, none of their supersets become optimal in future.

In order to exclude a noticeable number of feasible candidate active sets which are not optimal from the combinatorial tree, a joint downward and upward method for exploration of the combinatorial tree is suggested in [17] based on finding all the adjacent critical regions of any critical region while avoiding the geometric computations. As it is explained in [4], critical regions can be considered as nodes of a finite, fully connected graph. There are no isolated regions that could not be reached by starting from any region and going from one neighbour to another neighbour. Thus we can explore the entire feasible space starting from anywhere, while all critical regions are guaranteed to be found. The downward and upward exploration method is based on the following theorem from [5].

**Theorem 2 (mpQP without Degeneracy):**

Consider an optimal active set \( \{i_1, i_2, \ldots, i_k\} \) and its corresponding minimal representation of the critical region \( CR_0 \). Let \( CR_i \) be a full-dimensional neighbouring critical region to \( CR_0 \) and assume LICQ holds on their common
Critical regions in a non-degenerate system

Fig. 2: Combinations of optimal active constraints in adjacent critical regions in a non-degenerate system

As it is suggested in [17]. In accordance with our work in [18], we suggest an alternative approach for handling degenerate cases rather than post-processing in the next section. This approach is not based on geometric operations and hence is faster and more reliable when the number of parameter variables and the number of constraints increases.

III. MPQP ALGORITHM WITH DEGENERACY HANDLING

Theorem 2 implies that when the optimal active sets in two adjacent full-dimensional CRs differ in more than one constraint, at least one of the LICQ condition or SCS condition is violated. In order to explain different degenerate cases that might happen in the problem and propose proper methods for handling each of them, let us split different combinations of optimal active constraints in two adjacent critical regions which do not fulfill the conditions of Theorem 2 into two categories.

Categ. I: Let $CR_i$ and $CR_j$ be two adjacent critical regions with the corresponding optimal sets $A_i$ and $A_j$, respectively. If $|(A_i \setminus A_j)| \neq |(A_j \setminus A_i)| = 1$ where $| \cdot |$ denotes the cardinality of a set, then $CR_i$ and $CR_j$ lie in Categ. I.

Categ. II: Let $CR_i$ and $CR_j$ be two adjacent critical regions with the corresponding optimal sets $A_i$ and $A_j$, respectively. If $\max |(A_i \setminus A_j), |(A_j \setminus A_i)| \geq 2$, then $CR_i$ and $CR_j$ lie in Categ. II.

For all adjacent CRs classified in Categ.I, the following theorem states the two possible circumstances which can be characterised on their common facet.

Theorem 3 (Categ. I degeneracy)

Let two full-dimensional neighbouring CRs with the minimal representation be classified as Categ. I, i.e., the optimal active sets in these two regions can be defined by $A_i = [i_1, \ldots, i_k, i_{k+1}]$ and $A_j = [i_1, \ldots, i_k, i_{k+2}]$. Then one of these conditions holds:

a) LICQ is violated for the combination of optimal active constraints on their common facet.

b) LICQ holds on the common facet and SCS is violated for the optimal sets of those two CRs.

Proof: Since the combinations of the optimal active constraints in two adjacent CRs differ in more than one constraint, the possibility of violation of LICQ condition on the common facet follows directly from Theorem 2. Now, assume that LICQ holds on the common facet $F$. If none of the constraints in $A_i$ are weakly active, then we have that $\lambda^p > 0$, $\forall p \in \{1, \ldots, k+1\}$. Furthermore, inactiveness of $i_{k+1}$ in $CR_j$ leads in $\lambda_{k+1} = 0$ for $x \in CR_j$ and since $\lambda^{k+1}$ is continuous due to Theorem 1 and the fact that LICQ holds on the common facet, $\lambda^{k+1}$ should be equal to zero on $F$ as well. This means that the common facet for $CR_i$ can be expressed by $\lambda^{k+1} \geq 0$. On the other hand, if there is no constraint being weakly inactive in $A_i$, we have $G^{k+2}x^* < S^{k+2}x + W^{k+2}$, $\forall x \in CR_i$ except from on the common facet where $G^{k+2}x^* = S^{k+2}x + W^{k+2}$ (since $i_{k+2}$ is active in $A_j$), and due to continuity of the optimizer) Hence, $G^{k+2}x^* \leq S^{k+2}x + W^{k+2}$ is also defining the common facet for $CR_i$. This contradicts with the minimal representation of...
**Theorem 4** (Categ.II degeneracy)

Let two full-dimensional neighbouring CRs be classified as Categ. II, i.e., the optimal active set in one of the regions have at least two constraints which do not appear in the optimal set of the adjacent CR. Then SCS condition is violated on $F$, i.e., the common facet between these two critical regions.

**Proof:** Let us denote the critical region containing at least two constraints which do not appear in the optimal active set of the neighbouring critical region as $CR_i$, those two constraints as $i_{k+1}$ and $i_{k+2}$, and $A_j$ as the optimal active set in the adjacent critical region $CR_j$. It can be proved that $A_{F_i} \triangleq A_j \cup i_{k+1}$ is an optimal active set on the common facet with the associated critical region $CR_{F_i}$ due to feasibility of the LP in (6) with $A_j$ for all $x \in F$ and the trivial value for $\lambda^{k+1}$ equal to zero (Note that $\lambda^{k+1} \neq 0$ gives a feasible point for LP in (6) with $A_{F_i} \triangleq A_j \cup i_{k+1}$ which guarantees the optimality of $A_{F_i}$ there. However, this does not declare that the obtained optimal value for $\lambda^{k+1}$ should be necessarily zero). Similarly it can be proved that $A_{F_j} \triangleq A_j \cup i_{k+1} \cup i_{k+2}$ is an optimal active set on $F$ with the trivial values $\lambda^{k+1} = \lambda^{k+2} = 0$ in (6) and the corresponding critical region $CR_{F_j}$. Since the optimizer $z^*(x)$ is unique due to positive definiteness of $H$, for all $x \in F$ we have that $G_{k+2}^t z^*(x) + s^{k+2} = S^{k+2} x + W^{k+2}$ with some $s^{k+2} \geq 0$ as $x \in CR_{F_j}$, and simultaneously we have $G_{k+2}^t z^*(x) = S^{k+2} x + W^{k+2}$ as $x \in CR_{F_i}$. This means that $s^{k+2} = 0$ for all $x \in CR_{F_i}$, which completes the proof that $i_{k+2}$ is weakly inactive on $F$. □

**Remark 1.** Whenever the facet-to-facet property [20] does not hold for two adjacent critical regions, the same results as in Theorem 3 and Theorem 4 still hold by substituting $F$ with the part of the facet that is common between $CR_i$ and $CR_j$ in the proofs.

Exploiting the results in Theorem 3 and Theorem 4, we can now modify the downward-upward algorithm in [17] such that the degenerate cases are explicitly considered. As a result, all critical regions are found during exploration of the combinatorial tree while on average, the number of LPs needed to be solved reduces. To this aim, in the downward-upward exploration we consider combinations of active constraints for which either LICQ condition or SCS condition is violated as well. If in the exploration of the entire tree, no combination of active constraints with failure of SCS condition is found, then due to Theorem 4, no adjacent CRs which can be classified as Categ.II exists in the whole partitioned feasible parameter domain. Thus, the only possibility for the combinations of optimal active sets in two adjacent CRs, except for the cases for which degeneracy does not occur on their common facet, is due to Theorem 3-a. Hence one can explore the combinatorial tree up to level-$(\tilde{m} + 1)$ where $\tilde{m} = \min\{m, q\}$, simultaneously considering combinations of optimal active constraints for which LICQ is violated, and for all optimal sets with LICQ violation explore their subsets which have one constraint less and are not explored yet. This procedure guarantees the enumeration of all optimal active sets in such cases.

**Remark 2.** Note that the exploration of combinatorial tree up to level-$(\tilde{m} + 1)$, which is one level deeper than what is considered in the exploration method suggested by [10], is crucial for assuring that all optimal sets are enumerated. This is due to the fact that optimal sets which lie in the first category may appear in the last level of the combinatorial tree, i.e. level-$(\tilde{m})$, and the violation of LICQ condition takes place for the optimal active set in level-$(\tilde{m} + 1)$ forming the common facet between two adjacent critical regions. However, this does not impose significant computational burden to the problem as we built the lower levels using only the optimal sets (not all the feasible sets) in the level above.

On the other hand, if the SCS condition fails for some combinations of active constraints in a full-dimensional CR or in a lower-dimensional CR which corresponds to the common facet between full-dimensional CRs, identifying the combination of optimal active constraints in the adjacent CR is not straightforward. This is, in particular, due to the possibility of many overlapping lower-dimensional CRs which leads to a significantly different combination of active constraints in the full-dimensional adjacent CR. To make it more clear, consider the following example.

**Example 1** (Lower-dimensional critical regions with SCS violation): Fig. 3 shows the partition of the feasible parameter domain for the first example in [20]. As it can be seen, two full-dimensional CRs with the optimal sets $A_i = [1, 3, 6]$ and $A_j = [2, 4, 5]$ are adjacent, which shows 6 different constraints in the neighbouring critical regions. In other words, the combination of optimal active sets in these two regions are completely different. This is due to violation of the SCS condition in the overlapping lower-dimensional CRs which form the common facet (or part of it) between them. More detailed, a possible transition of combinations of optimal active constraints from $A_i$ to $A_j$ takes place via $A_i = [1, 3, 6] \rightarrow [1, 3, 5, 6] \rightarrow [1, 5, 6] \rightarrow [1, 2, 5, 6] \rightarrow [1, 2, 5] \rightarrow [1, 2, 4, 5] \rightarrow A_j = [2, 4, 5]$ where the SCS condition fails for all the intermediate optimal active sets and their corresponding CRs partially overlap. Fig. 4 depicts this overlapping lower-dimensional CRs.
will be found even if it is not found as an adjacent critical

to check the feasibility of non-optimal subsets as we are sure
of all these constraints is feasible. Therefore, there is no need
[10]. However, as we have observed a priori, the combination
exploration method of the combinatorial tree as suggested by
if they have not been already explored. This is the same
\( \tilde{C} \) rank subsets which have at most

\( \tilde{m} \) are weakly inactive for each optimal active set with violation of
SCS condition and then explore all its unexplored full row
rank subsets. This means that the
region of its other neighbouring critical regions. Note that
the indices of all weakly inactive constraints can be simply
obtained by identifying all slack variables equal to zero.
Theoretically, this can be done for every optimal set with
SCS failure separately. But as the constructed supersets
can share many constraints in common or even they can
be exactly identical (e.g., the supersets for all intermediate
optimal active sets in the above example are identical and
equal to \( \text{Sup} = [1, 2, 3, 4, 5, 6] \)), we have observed in the
numerical examples that it would be beneficial if we first
determine the union of all found supersets for optimal sets
with violation of SCS, and then explore all its unexplored full
row rank subsets as mentioned before. Consequently we avoid
constructing too many repetitive subsets. On the other hand, if
the cardinality of the obtained superset is considerably large
with respect to each of such sets, meaning that the sets with
SCS violation do not share many constraints, it can happen
that considering the sets with SCS violation individually
results in less computational complexity. The approximate
number of LPs that should be solved in each case can be
computed first in order to help choosing the best strategy.
Note that using the superset, the maximum number of
\( C(r, 1) + C(r, 2) + \cdots + C(r, n) \) LPs should be solved while
the number of required LPs considering each set separately is
approximately \( n_x \times [C(r_n, 1) + C(r_n, 2) + \cdots + C(r_n, n)] \),
where \( C(r, k) \) denotes the combination of \( k \) elements out of \( r \)
and \( n_x \), \( n_r \), and \( r_n \) are the cardinality of the superset, number
of control variables, number of sets with SCS violation and the
average cardinality of all sets with SCS violation, respectively.

The following theorem shows that it is not required to
consider the optimal active sets for which LICQ is violated
in the downward exploration of the combinatorial tree.

**Theorem 5**
If a superset \( A_l \) of an optimal active set \( A_j \) for which LICQ
is violated, is also optimal, then the SCS condition is violated
for the optimal active set \( A_j \).

Theorem 5 guarantees the enumeration of all sets which
have similar characteristics to \( A_l \) while dealing with their
subsets which are optimal with violation in SCS condition.
Hence it preserves us from solving the optimization problem
(6) for candidate active sets which can arise from exploring
the supersets of optimal sets with LICQ violation if it is not
needed. Before proceeding further, we state the following
lemma which gives us required tools for proving Theorem 5.

**Lemma 1.**
If the LICQ condition fails for the optimal active set \( A_i \) in a
full-dimensional critical region, then all its subsets \( A_j \subset A_i \)
with \( G^{A_j} \) having full row rank, are optimal active sets with
violation of the SCS condition.

**Proof:** Assume the full-dimensional critical region \( CR_i \)
with corresponding optimal set \( A_i = [i_1, \ldots, i_{k-1}, i_k] \) and the
Lagrange multipliers \( \{\lambda^1, \ldots, \lambda^K\} \) for which LICQ is violated.
Moreover, assume that \( A_j = [i_1, \ldots, i_{k-1}] \) is one of its full
row rank subsets. This means that the \( k^{th} \) row of matrix \( G^{A_i} \)

\[
\begin{bmatrix}
\end{bmatrix}
\]
can be written as $G^{A_i,k} = c_1 G^{A_i,1} + \ldots + c_{k-1} G^{A_i,k-1}$ where $G^{A_i,j}$ represents the $j^{th}$ row of matrix $G^{A_i}$. Let $x_0$ be a point in the interior of $CR_i$. Since $A_i$ is optimal at $x_0$, we have the optimality condition as $Hz^* + (G^{A_i,1})^T \lambda^1 + \ldots + (G^{A_i,k-1})^T \lambda^{k-1} + (G^{A_i,k})^T \lambda^k$. Using the equality $G^{A_i,k} = c_1 G^{A_i,1} + \ldots + c_{k-1} G^{A_i,k-1}$ we can rewrite the optimality condition as $Hz^* + (G^{A_i,1})^T \lambda^1 + \ldots + (G^{A_i,k-1})^T \lambda^{k-1} + (c_1 G^{A_i,1} + \ldots + c_{k-1} G^{A_i,k-1})^T \lambda^k = Hz^* + (G^{A_i,1})^T (\lambda^1 + c_1 \lambda^k) + \ldots + (G^{A_i,k-1})^T (\lambda^{k-1} + c_{k-1} \lambda^k)$. This means that $A_j = [i_1, \ldots, i_{k-1}]$ is also optimal active set at $x_0$ with $\lambda = \lambda^1 + c_i \lambda^k, \forall l \in \{1, \ldots, k-1\}$ and the slack variable corresponding to the $k^{th}$ constraint is equal to zero ($s^k = 0$). Hence $A_j = [i_1, \ldots, i_{k-1}]$ is an optimal set for which SCS does not hold.

Regarding Lemma 1 it is worth noting that an optimal active set for which LICQ is violated can have a full-dimensional critical region as pointed out in [1]. Such CRs can be obtained by a projection algorithm [See Appendix for more details]. The following example gives an illustration for these cases.

**Example 2** (LICQ violation in a full-dimensional CR): Consider the following mpQP:

\[ V_N^*(x) = \min_{x} \frac{1}{2} z^T z \]

s.t. \[ G \begin{bmatrix} 1 & 0 & -1 & 0.5 \\ -1 & 0 & 1 & 0.5 \\ 0 & 1 & -1 & 0.5 \\ 0 & -1 & -1 & 0.5 \end{bmatrix} z \preceq \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 1 \\ -1 \end{bmatrix} x + \begin{bmatrix} -1 \\ -1 \\ -1 \end{bmatrix} \]  

(7a)

and $-2 \leq x_i \leq 2; i = 1, 2, 3, 4$

where $n_z = 4$ indicates that up to 4 different constraints can appear in the optimal active sets with full-dimensional CRs. Fig. 5a shows the critical region corresponding to the optimal set $A = \{1, 2, 3, 4\}$ which is obtained by projection. Based on Lemma 1, we expect that any arbitrarily chosen subset of $A$ with 3 constraints should be degenerate in the sense of SCS violation. The simulation results meet this expectation and confirm that for all optimal sets $A_1 = \{1, 2, 3\}, A_2 = \{1, 2, 4\}, A_3 = \{1, 3, 4\}$ and $A_4 = \{2, 3, 4\}$ SCS condition is violated while their corresponding CRs are full-dimensional as shown in Fig. 5b.

Lemma 1 proves that an optimal set with violation of LICQ condition ($A_j$), built by adding one feasible constraint to an optimal set for which both LICQ and SCS hold, should be lower-dimensional. The low-dimensionality of $A_j$ is then used in the proof of Theorem 5 as follows:

**Proof (Theorem 5):** Assume that $A_i = [i_1, \ldots, i_k]$ is an optimal active set with a full-dimensional critical region $CR_i$, where both LICQ and SCS conditions hold. Further assume that its superset $A_j = [i_1, \ldots, i_k, i_{k+1}]$ is an optimal active set with violation of the LICQ condition. By Lemma 1 it is clear that the corresponding critical region $CR_j$ cannot be fully-dimensional since otherwise, SCS condition should fail for $A_i$. Then if $A_i = [i_1, \ldots, i_{k+2}]$ which is built by adding the feasible constraint $i_{k+2}$ to $A_j$ is also optimal with $CR_i$, two different situations may happen. i) $CR_i$ is low-dimensional: This means that two low-dimensional critical region $CR_j$ and $CR_i$ are neighbouring. Therefore they must overlap. Hence $i_{k+2}$ is weakly inactive for $A_j$. ii) $CR_i$ is full-dimensional: This means that $CR_i$ and $CR_j$ are two full-dimensional CRs which are adjacent. Therefore they lie in the Categ.II and the SCS condition fails on their common facet (with $A_j$) as a result of Theorem 4.

Based on the above theories, the downward-upward algorithm can be summarized as in Algorithm 1.

**IV. SIMULATION RESULTS**

In this section, the simulation results of the combinatorial approach using the suggested method in Algorithm 1 for three different cases are shown and compared with other methods implemented in MPT3.

**Case 1:** As the first case, we consider the fuel cell breathing control system with 8 state variables and 1 input and discretize it with $T_d = 1$ sec. This case does not have optimal sets in which SCS fails. However, the condition in Theorem 3-a occurs in the fuel cell system with $N = 6$ in which $\tilde{m} = 3$ and $A_i = [3, 11, 13]$ and $A_j = [11, 13, 16]$ are the optimal sets in two full-dimensional adjacent CRs and $A_F = [3, 11, 13, 16]$ is the optimal set on their common facet with the violation of the LICQ condition as $|A_F| > \tilde{m}$. Algorithm 1 is implemented in MATLAB using GLPK, intended for solving large-scale linear programming, as the LP solver. The simulation results using this routine and the algorithm in [10], implemented in
Algorithm 1: Downward-upward exploration strategy of the combinatorial tree

Phase I (Initialization):
1) $i = 1$. Explore the entire level-1, use (6) to check the optimality of each constraint. For each optimal constraint with violation of the SCS condition, create its superset including the active and all weakly inactive constraints and store it in “SCS Set”. If the constraint is not optimal, use (6) without optimality conditions to check the feasibility of that constraint. Store all optimal constraints for which the SCS condition holds in “Optimal Set” and all feasible constraints, whether they are optimal or not, in “Feasible Set”;
   - if no constraint is found to be optimal without violation of SCS condition in 1), then:
     - while Optimal Set is empty, explore the entire level-$(i+1)$, check only for optimality of the generated combinations. For each found optimal set with violation in SCS condition, create its superset including all active and weakly inactive constraints and store them in SCS Set;
   - $i := i + 1$;

Phase II (Recursive Exploration):
2) (Downward Exploration) Construct level-$(i+1)$ by adding one feasible constraint from level-1 to all sets in Optimal Set which are found in level-$i$ and check only for the optimality of new combinations whether LICQ holds for them or not. For each optimal active set which is found during this step:
   - if both LICQ and SCS hold (Theorem 2) compute control law and critical region, and add the combination to Optimal Set;
   - elseif SCS fails (Theorem 4) compute the superset including all active and weakly inactive constraints, and add it to SCS Set; the combination to Optimal Set;
   - elseif LICQ fails (Theorem 3-a and Theorem 5) add it to LICQ Set and explore only its subsets with one element less and check for the optimality, add all found optimal sets to New Set;
   - if New Set is empty then go to 5), else go 4);

Phase III (Handling Cases with SCS Violation):
5) Compute the union of all sets in SCS Set. Explore all its full row rank subsets with cardinality less than or equal to $\tilde{m}$ if it is not enumerated yet;
   - add all newly found optimal active set for which SCS holds to Optimal Set and go to 4);
   - if no new set for which SCS holds is found, stop.

MPT3, on a 3.2 GHz core i5 CPU running MATLAB 2014a are shown in Table I, where $N$, $n_{CR}$, $n_{LP}$ and $SF$ represent the prediction (and control) horizon, number of found CRs, number of solved LPs and the speedup factor defined as the ratio of the computational time using algorithm in [10] to the computational time using the suggested algorithm here. It can be seen that as the prediction horizon increases, the speedup factor increases dramatically which indicates the superiority of the suggested algorithm for systems with a large number of constraints.

Case 2: As an example for cases with violation of SCS condition, we augmented example 1 from [20] by adding random matrices to $G$, $S$ and $W$ such that the number of inputs and the number of constraints are increased in the problem. Table II shows the comparison for four different randomly augmented examples for which SCS condition fails for some of the combinations of active constraints. Here $n_z$, $q$, $n_{CR}$, $n_{LP}$, $t_{comp}$ and $SF$ represent the number of control variables, number of constraints, number of found CRs, number of solved LPs, computational time required by different algorithms and speedup factor, respectively. It can be seen that the suggested algorithm has a significant reduction

**Table I: Comparison between different algorithms for fuel cell breathing system**

<table>
<thead>
<tr>
<th>Method</th>
<th>$N$</th>
<th>$n_{CR}$</th>
<th>$n_{LP}$</th>
<th>$t_{comp}$</th>
<th>$SF$</th>
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</thead>
<tbody>
<tr>
<td>Alg. 1</td>
<td>3</td>
<td>71</td>
<td>574</td>
<td>2.7608</td>
<td>0.7298</td>
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<tr>
<td>Alg. 2</td>
<td>71</td>
<td>287</td>
<td>2.0150</td>
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<td></td>
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**Table II: Comparison between different algorithms for fuel cell breathing system**

<table>
<thead>
<tr>
<th>Method</th>
<th>$N$</th>
<th>$n_{CR}$</th>
<th>$n_{LP}$</th>
<th>$t_{comp}$</th>
<th>$SF$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alg. 1</td>
<td>4</td>
<td>133</td>
<td>151</td>
<td>5.9922</td>
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<tr>
<td>Alg. 2</td>
<td>133</td>
<td>1701</td>
<td>5.0730</td>
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</tr>
</tbody>
</table>

Alg.1: Algorithm suggested here
Alg.2: Algorithm by Gupta et al.
TABLE II: Comparison between different algorithms for the system with violation in the SCS condition

<table>
<thead>
<tr>
<th>Method</th>
<th>$n_x$</th>
<th>$q$</th>
<th>$n_{CR}$</th>
<th>$n_{LP}$</th>
<th>$t_{comp}$ [s]</th>
<th>SF</th>
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<tr>
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</tr>
<tr>
<td>Alg. 1</td>
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<td>70</td>
<td>1763</td>
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<tr>
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<tr>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>6439332*</td>
<td>5h*</td>
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</table>

* Matlab ran out of memory in the ninth-level, after approximately 5 hours of execution and solving 6439332 LPs.

Alg.1: Algorithm suggested here
Alg.2: Algorithm by Gupta et al.

TABLE III: Comparison between different algorithms for the system in (8)

<table>
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<tr>
<th>Method</th>
<th>$N$</th>
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<th>$n_{CR}$</th>
<th>$t_{enum}$ [s]</th>
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<td></td>
<td></td>
<td></td>
<td>1.6530</td>
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<tr>
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<td>72.8494</td>
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</tbody>
</table>

* Matlab ran out of memory in the ninth-level, after approximately 8 hours of execution.

of computational time in comparison with the algorithm in [10] for the combinatorial approach and as the the number of control variables and the number of constraints increase, the superiority of the suggested algorithm becomes significantly noticeable.

Case 3: In the following, we show how Algorithm 1 compares to other methods for solving mpQP implemented in MPT3, i.e. the geometric approach using the function mptsolve, the enumeration based method of [10] using function mpt-enumpqp and the enumeration based partial complementarity problem using function mpt-enump-plcp. The simulations are performed by considering the example in [13], i.e. a mpQP constructed from the typical MPC setup of the form

\[
\min_{u_0, \cdots, u_{N-1}} x_T^T P x_N + \sum_{k=0}^{N-1} x_k^T Q x_k + u_k^T R u_k
\]  
\[
\text{s.t. } x_{k+1} = A x_k + B u_k
\]  
\[
x \in X, u \in U
\]  

with \(x \in \mathbb{R}^{n_x}, u \in \mathbb{R}, P = Q = I_{n_x}, R = 1, X = \{ x | -10 \leq x_i \leq 10, \ i = 1, \cdots, n_x \}, U = \{-1 \leq u \leq 1 \}.\) The prediction model (8b) is obtained by discretizing the model 1/(s + 1)^{n_x} with sampling time of 1 second and then converting the discretized model to a state-space form. The number of optimization variables depends on the control horizon \(N\). Different values for \(n_x\) and \(N\) are considered in simulations in order to assess the performance of various parametric solvers for varying dimension of the parameter space and optimization variables. Simulation results are summarized in Table III, where \(t_{enum}\) and \(t_{tot}\) indicate the required time for enumerating all optimal active sets and the total time needed for enumerating all optimal active sets and creating their corresponding CRs. It can be seen that for low dimensional parameter spaces, the geometric approach succeeds to find all critical regions with a small computational time, which indicates its priority for such cases. The computational time of the suggested method in these cases, however, is not far from the computational time for geometric approaches, specially when building the critical regions is not of interest, e.g. in region-free explicit model predictive control. It can be seen that for cases having a higher number of parameters, the enumeration based methods show better performance in finding all CRs. While the method by [10] does not scale well with increasing control horizon in terms of the computational time, the suggested method is able to find the complete solution in a considerably shorter time.

V. CONCLUSION

In this paper, a new enumeration-based method for solving the mpQP problems was suggested based on exploiting the properties of full-dimensional adjacent critical regions. By excluding a large number of feasible but not optimal combinations of active constraints from the combinatorial tree, the computational time decreases dramatically while all critical regions in both non-degenerate and degenerate cases are guaranteed to be found. Furthermore, its enumerative nature makes it a suitable method for region-free explicit model predictive control purposes. Simulation results confirm the efficiency and priority of the suggested method for problems with a large number of parameters and constraints.

APPENDIX

CRITICAL REGION OF AN OPTIMAL ACTIVE SET WITH VIOLATION OF LINEAR INDEPENDENT CONSTRAINTS QUALIFICATION

Consider the multi-parametric quadratic program in (1) and the optimal active set \(A\) such that the rows of \(G^A\) are linearly dependent. Since \(G^A H^{-1}(G^A)^T\) is not invertible due to rank deficiency, the KKT conditions in (3) do not lead directly to (5a) and (5b), but only to a polyhedron expressed in the \((\lambda, x)\)-space which can be lower-dimensional or full-dimensional. In the sequel, the conditions under which the critical region is forced to be lower-dimensional is investigated. The optimality condition in (3a) yields \(z = -H^{-1}(G^A)^T \lambda\). Inserting this to (3b), we will have the following equality which must hold for the optimal set \(A\):

\[
-G^A H^{-1}(G^A)^T \lambda - S^A x - W^A = 0
\]
Denoting $-G^AH^{-1}(G^A)^T\lambda = U\Sigma V^T$, using singular value decomposition, where $U$ and $V$ are unitary matrices and $\Sigma$ is a rectangular diagonal matrix with non-negative real numbers on the diagonal, we can rewrite (9) as:

$$U\Sigma V^T\lambda = S^Ax + W^A$$  \hspace{1cm} (10)

Since $U$ is unitary matrix and hence invertible, (10) reads:

$$\Sigma V^T\lambda = U^{-1}S^Ax + U^{-1}W^A$$  \hspace{1cm} (11)

For a rank deficient matrix, $\Sigma$ has $p$ zero rows where $p$ is difference between number of rows in $-G^AH^{-1}(G^A)^T$ and its row rank. For simplicity, assume that $p = 1$. This means $\Sigma$ has one zero row, and the same holds for $\Sigma V^T$, i.e., $\Sigma V^T = \begin{bmatrix} \Sigma \\ 0 \end{bmatrix}$. Using this, we can rewrite the equality constraints of (11) as follows:

$$\tilde{\Sigma}\lambda = S_1x + W_1$$  \hspace{1cm} (12a)

$$0 = S_2x + W_2$$  \hspace{1cm} (12b)

Where $\begin{bmatrix} S_1 \\ S_2 \end{bmatrix} = U^{-1}S^A$ and $\begin{bmatrix} W_1 \\ W_2 \end{bmatrix} = U^{-1}W^A$.

Regarding (12b), different cases may happen:

- If $S_2 \neq 0$, the critical region of optimal set $A$ will be lower-dimensional since (12b) imposes a restriction on the values of state variables.
- If $S_2 = 0$ and $W_2 = 0$, (12b) evidently holds. Therefore, the critical region can be full-dimensional as there is no restriction on the values of state variables. This full-dimensional critical region can be obtained by a projection algorithm [21] which projects the polyhedron expressed in the $(\lambda, x)$-space, resulted from KKT conditions, onto the state space.
- The case $S_2 = 0$ and $W_2 \neq 0$ leads to infeasibility and thus to a contradiction since $A$ is assumed to be a feasible active set.

Consider for illustration Example 2 and the optimal active set $A = [1, 2, 3, 4]$ for which $G^AH^{-1}(G^A)^T$ is rank deficient. For this case, we have $S_2 = 0$. Hence (12b) yields $0 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + 0$ which does not impose any restriction on state variables. Therefore, the corresponding critical region can be full-dimensional. Fig. 6 shows this CR, obtained by firstly computing its representation in $(\lambda, x)$-space and then projecting it on $x$-space using the command projection of MPT3.

Let us now change the last row of matrix $S$ in Example 2 to $[1 \\ 1]$. From (12b) we have $0 = \begin{bmatrix} 0.5 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + 0$. This enforces $x_1$ to be zero over the entire critical region of optimal set $A$. Therefore, this CR is lower-dimensional (as $x_1$ is constant). Fig. 7a depicts the critical regions of the this new problem, and Fig. 7b shows the CR for $A = [1, 2, 3, 4]$ which is obtained by projection.

Besides, the latter case can be considered as another example for the critical regions in Categ II and the associated
Theorem 4. Based on the definition of Categ II, the adjacent critical regions with optimal sets $A = [1, 3, 4]$ and $A = [1, 2, 3]$ lie in Categ II. The same holds for the critical regions with optimal sets $A = [1, 3, 4]$ and $A = [1, 2, 4]$. Hence, we expect to have SCS violation on the common facets of these CRs due to Theorem 4. Results from solving LP in (6) for $A = [2, 3, 4]$ is consistent with this expectation as it yield $s^2 = 0$. This implies that constraint $\{1\}$ is weakly inactive on the entire critical region of $A = [2, 3, 4]$ which exactly overlaps the critical region of $A = [1, 2, 3, 4]$ shown in Fig. 7b.

ACKNOWLEDGMENT

The authors would like to thank the contribution of the People Programme (Marie Curie Actions) of the European Union’s Seventh Framework Programme (FP7/2007-2013) under REA grant agreement no 607957 (TEMPO), and the Research Council of Norway, Statoil, DNV GL and Sintef through the Centers of Excellence funding scheme, Grant 223254 - Centre for Autonomous Marine Operations and Systems (AMOS) for the financial support.

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Parisa Ahmadi-Moshkenani received her B.Sc. and M.Sc. degrees in electrical engineering from Sharif University of Technology, Tehran, Iran in 2007 and 2010, respectively. From 2014, she is pursuing a Ph.D. degree in the department of engineering cybernetics at Norwegian University of Science and Technology, working as an Early Stage Researcher (ESR) in Marie Curie Initial Training Network on Embedded Model Predictive Control and Optimization (ITN-TEMPO). Her research interests are optimization-based control, multi-parametric programming and explicit model predictive control.

Tor Arne Johansen received the MSc degree in 1989 and the PhD degree in 1994, both in electrical and computer engineering, from the Norwegian University of Science and Technology, Trondheim, Norway. From 1995 to 1997, he worked at SINTEF as a researcher before he was appointed Associate Professor at the Norwegian University of Science and Technology in Trondheim in 1997 and Professor in 2001. He has published several hundred articles in the areas of control, estimation and optimization with applications in the marine, aerospace, automotive, biomedical and process industries. In 2002 Johansen co-founded the company Marine Cybernetics AS where he was Vice President until 2008. Prof. Johansen received the 2006 Arch T. Colwell Merit Award of the SAE, and is currently a principal researcher within the Center of Excellence on Autonomous Marine Operations and Systems (NTNU-AMOS) and director of the Unmanned Aerial Vehicle Laboratory at NTNU.

Sorin Olaru is a Professor at CentraleSupélec, member of the CNRS Laboratory of Signals and Systems and of the INRIA team DISCO, all these institutions being part of the Paris-Saclay University in France. His research interests are encompassing the optimization-based control design, set-theoretic characterization of constrained dynamical systems as well as the numerical methods in control. He is currently involved in research projects related to embedded predictive control, fault tolerant control and time-delay systems.