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On the Feasibility of Linear Discrete-Time Systems of the Green Scheduling Problem

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On the Feasibility of Linear Discrete-Time Systems of the Green Scheduling Problem

Abstract
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Keywords
green scheduling; feasibility;

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On the Feasibility of Linear Discrete-Time Systems of the Green Scheduling Problem

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Abstract—Peak power consumption of buildings in large facilities like hospitals and universities becomes a big issue because peak prices are much higher than normal rates. During a power demand surge an automated power controller of a building may need to schedule ON and OFF different environment actuators such as heaters and air quality control while maintaining the state variables such as temperature or air quality of any room within comfortable ranges. The green scheduling problem asks whether a scheduling policy is possible for a system and what is the necessary and sufficient condition for systems to be feasible. In this paper we study the feasibility of the green scheduling problem for HVAC (Heating, Ventilating, and Air Conditioning) systems which are approximated by a discrete-time model with constant increasing and decreasing rates of the state variables. We first investigate the systems consisting of two tasks and find the analytical form of the necessary and sufficient conditions for such systems to be feasible under certain assumptions. Then we present our algorithmic solution for general systems of more than two tasks. Given the increasing and decreasing rates of the tasks, our algorithm returns a subset of the state space such that the system is feasible if and only if the initial state is in this subset. With the knowledge of that subset, a scheduling policy can be computed on the fly as the system runs, with the flexibility to add power-saving, priority-based or fair sub-policies.

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I. INTRODUCTION

Peak power consumption of buildings in large facilities like hospitals and universities becomes a big issue because peak prices are much higher than normal rates. Thus peak power consumption is directly related to the energy bill. [1]’s study on the power market data in the Pennsylvania-New Jersey-Maryland territory in 2006 suggests that if the peak load is reduced by 4.8% on average then the total expense would be cut by 3.5% or $1.2 billion. During a power demand surge an automated power controller of a building may need to schedule ON and OFF different environment actuators such as heaters and air quality control while maintaining the state variables such as temperature or air quality of any room within comfortable ranges.

However, some systems may not be feasible by any scheduling policy. For instance, consider the scenario where a controller in a building can power ON at most one heater any time and there are two rooms (with two separate heaters) whose temperatures are so low that both will drop below their lower thresholds in one time unit if the rooms are not heated. In this scenario the system is deemed to fail after one time unit. [2] formularizes this kind of scheduling problems, referred to green scheduling, and it presents a necessary and sufficient condition in continuous time domain for any system to be feasible. However, when time is discretized additional conditions are required.

In this paper, we present our research on linear discrete-time green scheduling systems. We built our work on the previous problem formulation by [2]–[4] and the geometric interpretation of the problem by [2], [3]. We derive an analytical form of the necessary and sufficient conditions for 2D systems to be feasible under certain assumptions. We also designed an algorithmic solution for general systems of $n$ tasks ($n \geq 2$). Given the increasing and decreasing rates of the tasks, our algorithm returns a subset of state space such that the system is feasible if and only if its initial state is in this subset. With the knowledge of that subset, a scheduling policy can be computed on the fly as the system runs, with the flexibility to add power-saving, priority-based or fair sub-policies.

The paper is organized as follows. Section (II) gives the formulation of the green scheduling problem. In Section (III) we explain our work on systems of two tasks and introduce some key concepts and ideas for solving general systems of $n$ tasks. In Section (IV) we present our algorithm for general systems of $n$ tasks. Our simulation results are shown in Section (V). In Section (VI) we note the related work. In the last section, we conclude.

II. TASK SYSTEM

In this section we rephrase the formulation of the green scheduling problem by [2]–[4] and the state space (or geometric) interpretation of the problem given by [2], [3].

A. Task Model

Consider a control system that controls temperature of a room within a certain range $[l, h]$ with a heater. Temperature is called the state variable of the control system. The control system could switch the heater ON or OFF. When the heater is ON, the temperature would change according to the dynamics of the system. For simplicity, here we assume the temperature increases linearly with rate $a$. Similarly, the temperature decreases linearly with rate $b$ when the heater is OFF. In this paper a “linear” system means the state variable increases or decreases linearly (constant slope) with respect to time. It is different from a “linear” system in control theory, where a state...
variable’s dynamics is characterized by a linear differential equation.

We construct the task model for such a control system as follows. A task \( T \) consists of a tuple of attributes \((x, l, h, x(0), M, a, b)\).

- \( x \): the state variable; \( x \in \mathbb{R} \).
- \( l, h \): the lower and upper threshold of the state variable; \( l, h \in \mathbb{R} \) and \( l < h \).
- \( x(0) \): the initial state; \( x(0) \in [l, h] \).
- \( M \): the mode of the task; \( M \in \{\text{ON}, \text{OFF}\} \).
- \( a, b \): the increasing (decreasing) rate of the state variable when the mode is ON (OFF); \( a, b \in (0, +\infty) \).

We assume that the attributes \( l, h, a \) and \( b \) of a task are fixed with respect to time. The mode of a task can be either ON or OFF at any time. The dynamic equation of the state variable is given by:

\[
\dot{x}(t) = \begin{cases} 
  a & \text{if } M(t) = \text{ON} \\
  -b & \text{if } M(t) = \text{OFF} 
\end{cases}
\]

In [2] a more general dynamic equation is given, in which the rates are not necessarily constant. In this paper we only consider linear trajectories.

A task is safe if and only if \( \forall t \geq 0, x(t) \in [l, h] \). A task fails if \( \exists t \geq 0, x(t) \notin [l, h] \).

B. Scheduling Problem

A task system \( S \) is a set of \( n \) (\( n \geq 1 \)) tasks \( \{T_i\} \) (\( i = 1, 2, \ldots, n \)). A scheduling policy \( \pi \) on \( S \) assigns the mode of each task in \( S \) for all \( t \geq 0 \). \( S \) is schedulable by a policy \( \pi \) if and only if under \( \pi \) every task in \( S \) is safe and at most one task is ON at any time. \( S \) is feasible if and only if there exists at least one scheduling policy under which \( S \) is schedulable. \( S \) is infeasible if and only if there is no scheduling policy under which \( S \) is schedulable. \( S \) fails at time \( t \) if at least one task in \( S \) fails at time \( t \).

Fig. 1 shows an example of scheduling a task system of two tasks. For simplicity, \( l_1 = l_2 = l \) and \( h_1 = h_2 = h \).

For a task system \( S \), we want to find the necessary and sufficient condition on its feasibility.

C. System State Space

For a task \( T_i \), define its normalized state variable \( \tilde{x}_i(t) = \frac{x_i(t) - l_i}{h_i - l_i} \). It follows that \( T_i \) is safe if and only if \( \tilde{x}_i(t) \in [0, 1] \) for all \( t \geq 0 \). Similarly, define normalized increasing and decreasing rates as \( \tilde{a}_i = \frac{a_i}{h_i - l_i} \) and \( \tilde{b}_i = \frac{b_i}{h_i - l_i} \), respectively. The dynamics of \( T_i \) becomes

\[
\dot{\tilde{x}}_i(t) = \begin{cases} 
  \tilde{a}_i & \text{if } M_i(t) = \text{ON} \\
  -\tilde{b}_i & \text{if } M_i(t) = \text{OFF} 
\end{cases}
\]

Consider a task system \( S \) of size \( n \) (\( n > 1 \)). Define system state \( X = [\tilde{x}_1 \, \tilde{x}_2 \, \ldots \, \tilde{x}_n]^T \), where \( T \) denotes transpose of matrix. Let \( X_i \) denote the \( i \)-th component of \( X \), i.e., \( X_i = \tilde{x}_i \). The dynamics of all task states can be reduced to the dynamics of the system state in a \( n \)-dimensional state space. For example, suppose during the time interval \([t, t + \Delta t]\), \( T_1 \) is ON while other tasks are OFF. The dynamics during the interval is given by \( \dot{\tilde{x}}_1 = \tilde{a}_1 \) and \( \dot{\tilde{x}}_i = -\tilde{b}_i \) (\( 2 \leq i \leq n \)). It is equivalent to \( X = [\tilde{a}_1 \, -\tilde{b}_2 \, \ldots \, -\tilde{b}_n]^T \). In other words, the system state \( X \) moves in the direction \( [\tilde{a}_1 \, -\tilde{b}_2 \, \ldots \, -\tilde{b}_n]^T \) in the state space during the interval. In the following context we also refer a system of \( n \) tasks as a \( n \)-dimensional system.

It follows that the system is safe if and only if the movement of the system state is restricted to a \( n \)-dimensional box in the state space for all time \( t \geq 0 \). We call this \( n \)-dimensional box safety box, denoted as \( \text{SafetyBox} \). We use the notation \( \text{Interval}_1 \times \text{Interval}_2 \times \cdots \times \text{Interval}_n \) to denote the set of states \( \{X | \forall i (1 \leq i \leq n), X_i \in \text{Interval}_i \} \). Thus,

\[
\text{SafetyBox} = [0, 1] \times [0, 1] \times \cdots \times [0, 1].
\]

D. Discrete Time Systems

Since practical systems are mostly scheduled and controlled by digital computers, we focus on discrete-time systems from now on. Let the unit time interval be \( \delta t \), and let \( \tilde{a}_i = \tilde{a}_i \cdot \delta t \) and \( \tilde{b}_i = \tilde{b}_i \cdot \delta t \). Then the normalized task state \( \tilde{x}_i \), either increases by \( \tilde{a}_i \) (ON) or decreases by \( \tilde{b}_i \) (OFF) during a unit time interval. In other words,

\[
\tilde{x}_i(k + 1) = \begin{cases} 
  \tilde{x}_i(k) + \tilde{a}_i & \text{if } M_i(k) = \text{ON} \\
  \tilde{x}_i(k) - \tilde{b}_i & \text{if } M_i(k) = \text{OFF} 
\end{cases}
\]

Let

\[
\begin{align*}
 g(0) &= [-\tilde{b}_1 \, -\tilde{b}_2 \, \ldots \, -\tilde{b}_n]^T \\
 g(i) &= [-\tilde{a}_1 \, \tilde{a}_i \, \tilde{a}_2 \, \ldots \, -\tilde{b}_n]^T \quad (1 \leq i \leq n)
\end{align*}
\]

The dynamic equation of a discrete time system is given by

\[
X(k + 1) = X(k) + g(k),
\]

where \( g(k) \in \{g(0), g(1), \ldots, g(n)\} \) and

\[
\begin{align*}
 g(k) &= \begin{cases} 
  g(0) & \text{iff all tasks are OFF} \\
  g(i) & \text{iff } T_i (1 \leq i \leq n) \text{ is ON while others are OFF}
\end{cases}
\end{align*}
\]

Fig. 2 illustrates the dynamics of a system state in the 2D safety box. We say that the system takes movement \( g(i) \) at time \( k \) if \( g(k) = g(i) \) (\( 0 \leq i \leq n \)).

By (4), a scheduling policy on a task system thus corresponds to a unique infinite sequence of movements the system takes at each time step: \( g(0)g(1) \ldots \). The feasibility of the
scheduling problem thus reduces to the restricted movement problem of the system state within the n-dimensional safety box.

**Theorem 1.** A n-dimensional discrete-time task system S is feasible if and only if given its initial system state \( X(0) \in \text{SafetyBox} \) and the set of possible movements \( G = \{g^{(0)}, g^{(1)}, \ldots, g^{(n)}\} \), there is an infinite sequence of movements \( g(0)g(1) \cdots \) such that \( \forall k \geq 0, X(k) \in \text{SafetyBox} \), provided that the dynamics of X is given by (3).

A benefit of this state space framework is that it frees us from considering the size of \( h_i - l_i \) for each task when addressing the feasibility of a system. The only things mattering are the initial system state and the possible movements. The reason is that from the scheduling point of view a task of larger or smaller \( h - l \) is always equivalent to a task of the original \( h - l \) but with a scaled initial state and scaled increasing and decreasing rates.

**E. Necessary and Sufficient Condition Problem**

Because a particular task system with a given scheduling policy and given \( X(0) \) and G can be modeled as a timed automaton, timed automata tools such as UPPAAL [5] might be used to verify its safety property. However, our goal in this paper is to find the necessary and sufficient conditions on \( X(0) \) for a task system to be feasible, and to synthesize a scheduling policy for it. We first investigate 2-dimensional task systems and introduce some key concepts and ideas that can be applicable to more general n-dimensional task systems. For 2-dimensional task systems we obtain necessary and sufficient conditions on both \( X(0) \) and G under certain assumptions. For n-dimensional task systems we design and implement an algorithm that given G computes a set of system states such that the system is feasible if and only if its initial state is in that set.

**III. 2D SYSTEMS**

Consider a 2-dimensional task system. The safety box is shown in Fig. 3. Define the critical zone of \( T_i \) as \([0, \tilde{b}_i) \times [0, 1)\) \((j \neq i)\), denoted as CriticalZone\(_i\). Thus, CriticalZone\(_1\) = \([0, \tilde{b}_1) \times [0, 1)\) and CriticalZone\(_2\) = \([0, 1) \times [0, \tilde{b}_2)\). Once \( X(k) \in \text{CriticalZone}_1 \), for \( X(k + 1) \in \text{SafetyBox} \) we must have \( g(k) = g^{(i)} \), otherwise \( X_i(k + 1) = X_i(k) - \tilde{b}_i < 0 \). In other words, \( T_i \) must be turned ON in its critical zone, otherwise it will fail at next time step. However, there are some region in the safety box that once the system state is inside the region at time \( k \) the system must fail at time \( k + 1 \) no matter what \( g(k) \) is. We call such region dead region, denoted as DeadRegion. Note that we use the word region to denote a subset of the safety box.

One obvious dead region for any 2D system is the intersection of the two critical zones, shown in Fig. 3a. We call these dead regions Type 1 dead regions. That is,

\[
\text{DeadRegion}(\text{Type 1}) = [0, \tilde{b}_1) \times (0, \tilde{b}_2).
\]

However, if \( \tilde{a}_i + \tilde{b}_i > 1 \), other parts of CriticalZone\(_i\) would also form a dead region, namely, \([1 - \tilde{a}_i, \tilde{b}_i) \times [0, 1)\), because task \( T_i \) cannot be turned ON in that region due to its upper threshold limitation (Fig. 3b). We group these dead regions into Type 2 dead regions. That is,

\[
\text{DeadRegion}(\text{Type 2}) = [1 - \tilde{a}_i, \tilde{b}_i) \times [0, 1)\) for \( i, \tilde{a}_i + \tilde{b}_i > 1 \).

In the following discussion on 2D systems, we make the following assumption:

**Assumption 1.** \( \forall i (1 \leq i \leq 2), \tilde{a}_i + \tilde{b}_i \leq 1 \).

This assumption guarantees that if \( T_i \) is turned ON anywhere in its critical zone at time \( k \), the task itself will not fail at time \( k + 1 \), although it does not guarantee that the whole system will not fail at time \( k + 1 \). The assumption also implies that we would only consider Type 1 dead region in our 2D systems discussion.

[2] has shown that a necessary condition for a n-dimensional system to be feasible is

\[
\sum_{i=1}^{n} \frac{\tilde{b}_i}{\tilde{a}_i + \tilde{b}_i} \leq 1.
\]

In 2D system, this is equivalent to

\[
\frac{\tilde{a}_1}{\tilde{b}_1} + \frac{\tilde{a}_2}{\tilde{b}_2} \geq 1.
\]

We will show that this condition plus the condition that the initial state is in certain region would form the necessary and sufficient condition for a 2D system to be feasible.
Thus, if \( X(k) \in PredeadRegion \) and all tasks are OFF at time \( k \), then \( X(k + 1) \in DeadRegion \). See Fig. 4a for illustration.

Let \( \hat{a}_{\sigma} \) denote the tight upper bound of a region in direction \( \hat{x}_i \). For example, \( \hat{a}(DeadRegion, 1) = b_1 \) and \( \hat{a}(PredeadRegion, 1) = 2b_1 \).

**Assumption 2.** \( \exists \sigma (1 \leq \sigma \leq 2), \hat{a}(PredeadRegion, \sigma) + \hat{a}_{\sigma} < 1 \).

This assumption guarantees that if \( X(k) \in PredeadRegion \) we can always turn ON \( T_\sigma \) and the system will still stay in the \( SafetyBox \) at time \( k + 1 \) without surpassing the upper threshold of \( T_\sigma \).

Define the following regions:

\[
\begin{align*}
\text{DangerRegion}_i &= \text{CriticalZone}_i \setminus \text{DeadRegion} \ (i = 1, 2) \\
\text{RelaxRegion} &= \text{SafetyBox} \setminus \\
&= (\text{CriticalZone}_1 \cup \text{CriticalZone}_2) \\
&\cup \text{PredeadRegion})
\end{align*}
\]

Fig. 4a illustrates these regions. It can be shown that the safety box is the union of the following 5 disjoint regions:

\[
\begin{align*}
\text{SafetyBox} &= \text{DeadRegion} \cup \text{PredeadRegion} \\
&\cup \text{DangerRegion}_1 \cup \text{DangerRegion}_2 \\
&\cup \text{RelaxRegion}.
\end{align*}
\]

We refer to this fact as decomposition of the safety box. We now present our premier 2D scheduling policy.

**Premier 2D Scheduling Policy:** for all \( k \geq 0 \)

\[
g(k) = \begin{cases} 
  g^{(i)} & \text{if } X(k) \in \text{DangerRegion}_i \\
  g^{(\sigma)} & \text{if } X(k) \in \text{PredeadRegion} \\
  g^{(0)} & \text{if } X(k) \in \text{RelaxRegion}
\end{cases}
\]

Fig. 4b illustrates the premier 2D scheduling policy by assuming \( \sigma = 1 \). Scheduling on \( \text{DeadRegion} \) is omitted because it fails at time \( k + 1 \) anyway.

**Proposition 1.** Suppose Assumption 1 and Assumption 2 hold. If \( X(k) \in \text{SafetyBox} \setminus \text{DeadRegion} \) (\( k \geq 0 \)), then under the premier 2D scheduling policy, \( X(k + 1) \in \text{SafetyBox} \setminus \text{DeadRegion} \).

**Proof:** \( X(k) \) must be in one of the other 4 disjoint regions in \( SafetyBox \) by the decomposition of the safety box. We now prove the proposition holds for \( X(k) \in \text{DangerRegion}_1 \). Proofs for other regions are similar. By definition \( \text{DangerRegion}_1 = [0, \hat{b}_1] \times [\hat{b}_2, 1)_2 \). Under the premier 2D scheduling policy, \( g(k) = g^{(1)} = [\hat{a}_1 - \hat{b}_2] \).

\[
X(k + 1) = X(k) + g^{(1)} = [\hat{a}_1, \hat{b}_1 + \hat{a}_1] \times [0, 1 - \hat{b}_2]_2 \equiv D
\]

Obviously \( D \subset \text{SafetyBox} \), and \( D \cap \text{DeadRegion} = \emptyset \) because \( \hat{a}_1 > \hat{b}_1 \). Thus, \( X(k + 1) \in \text{SafetyBox} \setminus \text{DeadRegion} \).

**Lemma 1.** Suppose Assumption 1 and Assumption 2 hold. A system satisfying \( u_1 \geq 1 \wedge u_2 \geq 1 \) is feasible if and only if \( X(0) \in \text{SafetyBox} \setminus \text{DeadRegion} \).

**Proof:** The “only if” part is trivial. For the “if” part, we can apply Proposition 1 to prove the system is schedulable under the premier 2D scheduling policy.

**B. Case** \( u_1 < 1 \wedge u_2 \geq \left\lfloor \frac{1}{u_1} \right\rfloor + 1 \)

Since \( \hat{a}_1 < \hat{b}_1 \), some states in \( \text{DangerRegion}_1 \) can reach \( \text{DeadRegion} \) in one time step by taking \( g^{(1)} \), namely the states in \( [0, \hat{b}_1 - \hat{a}_1] \times [\hat{b}_2, 2\hat{b}_2]_2 \equiv R_{0,1} \equiv \{ X | X \in \}

Suppose Assumption 1 and Assumption 3 hold.

Lemma 2. Suppose Assumption 1 and Assumption 3 hold. A system satisfying \( u_1 < 1 \) and \( u_2 \geq \left( \frac{1}{u_1} \right) + 1 \) is feasible if and only if \( X(0) \in \text{SafetyBox} \setminus \text{UnsafeRegion} \). UnsafeRegion is given by (12).

Proof: Similar to proof of Lemma 1, using the general 2D scheduling policy. The policy is shown in Fig. 4d.

C. Case \( u_1 < 1 \) and \( \frac{1}{u_1} \leq u_2 < \left( \frac{1}{u_1} \right) + 1 \)

Given a rectangular region \( D = [\theta_1, \theta_2] \times [\tau_1, \tau_2] \), define its width as \( \text{width}(D) = \theta_2 - \theta_1 \) and its height as \( \text{height}(D) = \tau_2 - \tau_1 \).

This case is more complicated than the previous case, because unless \( R_{0,0} \) does not exist, some states in DangerRegion12 can reach \( R_{0,0} \) in one time step by taking \( g(2) \), namely the states in \([\check{b}_1, \check{b}_1 + (\check{b}_1 - \check{\alpha}_1)]_1 \times [0, \check{b}_2 - (\check{\alpha}_2 - \check{\beta}_2)]_2 \equiv R_{1,0} \). Thus once \( X(k) \in R_{1,0} \), the system must fail by time \( k + \alpha + 2 \). This will in turn bring a series of regions \( R_{i,j} (1 \leq j \leq \alpha) \) into the unsafe region like in the previous case. Another series of regions \( R_{i,\alpha} \) would in turn be induced from \( R_{1,\alpha} \). The process goes on. However, the process must terminate. To see this, let us define these regions first. Define

\[
R_{i,j} = \left[ \check{b}_1 + (i - 1)(\check{b}_1 - \check{\alpha}_1), \check{b}_1 + i(\check{b}_1 - \check{\alpha}_1) \right] \times \left[ \check{b}_2 - (i\check{\alpha}_2 - \check{\beta}_2) \right]_2
\]

for \( 1 \leq i \leq \beta, 0 \leq j \leq \alpha \), where \( \beta = \left( \frac{\check{b}_2}{\check{\alpha}_2 - \check{\beta}_2} \right) \). Note that the above definitions and the definitions of \( R_{0,j} \) in (11) enforce that \( \forall j (1 \leq j \leq \beta), R_{0,j} \equiv \{ X | X \in \text{SafetyBox} \text{ and } X + g(2) \in R_{i-1,\alpha} \} \). And \( \forall j (1 \leq j \leq \alpha), R_{i,j} \equiv \{ X | X \in \text{SafetyBox} \text{ and } X + g(1) \in R_{i-1,j} \} \). It can be seen that \( \text{height}(R_{\beta,1}) = \check{b}_1 - i(\check{\alpha}_2 - \check{\beta}_2) \). Thus, \( \text{height}(R_{i+1,j}) < \text{height}(R_{i,j}) \). But since \( \text{height}(R_{\beta,1}) \) must be positive, the process must terminate at \( i = \beta \). Note also that \( \forall i, j (1 \leq i \leq \beta, 1 \leq j \leq \alpha), R_{i,j} \in \text{CriticalZone}_1 \). To show that, we only need to show \( u_b(R_{\beta,1}, 1) \leq \check{b}_1 \).

\[
u_b(R_{\beta,1}, 1) = \check{b}_1 + \beta(\check{b}_1 - \check{\alpha}_1) - \check{\alpha}_1 = \check{b}_1 + \check{\alpha}_1 \left( \frac{1}{u_2 - \alpha} \right) - \check{\alpha}_1 \\
\leq \check{b}_1.
\]

Define other regions by (13) and (14) as before. We can still decompose the safety box as given by (15).

Lemma 3. Suppose Assumption 1 and Assumption 3 hold. A system satisfying \( \left( \frac{1}{u_1} \right) \leq u_2 < \left( \frac{1}{u_1} \right) + 1 \) is feasible if and only if \( X(0) \in \text{SafetyBox} \setminus \text{UnsafeRegion} \). UnsafeRegion is given by (16).

Proof: Similar to proof of Lemma 1, using the general 2D scheduling policy. The policy is shown in Fig. 4f.

Combining the three lemmas, we obtain the following theorem.

Theorem 2. For all 2D systems that satisfy the condition (7), if Assumption 1 holds, then the unsafe region can be analytically determined by (16) and the safety box can be decomposed into...
5 disjoint regions by (15). If further Assumption 3 holds, then
the system is feasible if and only if \(X(0) \in \text{SafetyBox} \setminus \text{UnsafeRegion} \), and the system is schedulable by the general 2D scheduling policy.

IV. ALGORITHMIC SOLUTION TO GENERAL
\(n\)-DIMENSIONAL SYSTEM

For general \(n\)-dimensional systems, analytical forms of necessary and sufficient conditions on \(X(0)\) and \(G\) for systems to be feasible are difficult to get. However, based on the observation of 2D systems, we design and implement an algorithm that given any \(G\) (i.e., \(\{\tilde{a}_i, \tilde{b}_i\}\)) returns a region \(\text{UnsafeRegion}\) such that the system is feasible if and only if \(X(0) \in \text{SafetyBox} \setminus \text{UnsafeRegion}\). We will first show how to construct \(\text{UnsafeRegion}\) algorithmically and then prove it indeed has the above property.

Let \(\text{OutSafetyBox}\) denote the set of states out of the safety box. That is,

\[
\text{OutSafetyBox} = \{X | X \notin \text{SafetyBox}\}.
\]

A. Construct \(\text{UnsafeRegion}\)

For the simplicity of the following discussion, we use the word \(\text{rectangle}\) to refer to any set of the states of the form \([r_{10}, r_{11}] \times [r_{20}, r_{21}] \times \cdots \times [r_{n0}, r_{n1}]\). The intersection between two rectangles \(R_1 \cap R_2\) is the empty set \(\phi\) or another rectangle, while the set difference \(R_2 \setminus R_1\) returns the empty set (when \(R_2 \subseteq R_1\)) or a set of rectangles. Note that we enforce \(R_2 \setminus R_1 = \{R_2\}\) if \(R_1 \cap R_2 = \emptyset\). Define a function \(\text{shift}(R, v)\), which returns a rectangle as shifting rectangle \(R\) by a vector \(v\). That is,

\[
\text{shift}(R, v) \equiv \{X + v | X \in R\} = [r_{10} + v_1, r_{11} + v_1] \times [r_{20} + v_2, r_{21} + v_2] \times \cdots \times [r_{n0} + v_n, r_{n1} + v_n].
\]

Based on the observation on 2D systems, define the dead region of a \(n\)-dimensional system as

**Definition 1.** DeadRegion \(\equiv \{X | X \in \text{SafetyBox}\) and \(\forall i(0 \leq i \leq n), X + g^{(i)} \in \text{OutSafetyBox}\}.

Accordingly, define DeadRect as a rectangle such that

**DeadRect \(\subset\) SafetyBox and \(\forall i(0 \leq i \leq n), \text{shift}(\text{DeadRect}, g^{(i)}) \subset \text{OutSafetyBox}\)**

There are two types of dead rectangles. Type 1 dead rectangle

**DeadRect (Type 1) = [0, 1]_i \times \cdots \times [0, \tilde{b}_i]_j \times \cdots \times [0, 1]_n**

for \((1 \leq i \neq j \leq n)\). Type 2 rectangle

**DeadRect (Type 2) = [0, \tilde{a}_i]_i \times \cdots \times [1 - \tilde{a}_i, \tilde{b}_i]_j \times \cdots \times [0, 1]_n**

for any \(i\) such that \(\tilde{a}_i + \tilde{b}_i > 1\). Let DeadRectSet denote the set of all dead rectangles of both Type 1 and Type 2 of the system. Then the dead region of the whole system is

\[
\text{DeadRegion} = \bigcup_{R \in \text{DeadRectSet}} R.
\]  

(17)

From the discussion of 2D systems, we have learned that we can reduce the safety problem of individual system states to that of a rectangle: if all systems in a rectangle \(R\) are unsafe, then we say the rectangle is unsafe.

We denote the set of unsafe rectangles of a system as \(\text{UnsafeRectSet}\). We initialize the \(\text{UnsafeRectSet}\) to be DeadRectSet. If there exists a rectangle \(R\) such that

1. \(R \in \text{SafetyBox}\)
2. \(\forall R_{\text{unsafe}} \in \text{UnsafeRectSet}, R \setminus R_{\text{unsafe}} = \emptyset\)
3. \(\forall i(0 \leq i \leq n), \text{shift}(R, g^{(i)}) \subset \text{OutSafetyBox} \lor (R_{\text{unsafe}} \in \text{UnsafeRectSet}, \text{shift}(R, g^{(i)}) \subseteq R_{\text{unsafe}}), \) that is, once \(X(k) \in R\), then \(X(k + 1)\) is either out of the safety box or inside of a known unsafe rectangle,

then by induction \(R\) is also a unsafe rectangle, and so we append it into the \(\text{UnsafeRectSet}\). We call the above criteria unsafe criteria.

Beginning with DeadRectSet, we expand the \(\text{UnsafeRectSet}\) by looking for \(R\) that satisfies the unsafe criteria. Let \(R_{\text{unsafe}} \in \text{UnsafeRectSet}\). Consider the rectangle

\[
R_{\text{back}} = \text{shift}(R_{\text{unsafe}}, -g^{(i)}) \cap \text{SafetyBox}
\]

for some \((0 \leq i \leq n)\). It satisfies that \(R_{\text{back}} \subset \text{SafetyBox}\) and \(\text{shift}(R_{\text{back}}, g^{(i)}) \subseteq R_{\text{unsafe}}\). However, it may intersect with other known unsafe rectangles. Thus let

**workingSet = \emptyset**

and

\[
\forall R_{\text{unsafe}} \in \text{UnsafeRectSet}, \text{workingSet} = \text{workingSet} \cup (R_{\text{back}} \setminus R_{\text{unsafe}}).
\]

So \(\forall R_{\text{inwork}} \in \text{workingSet}, \text{R}_{\text{inwork}}\) satisfies the unsafe criteria (1) and (2). Then find any rectangle \(R_{\text{newUnsafe}} \subseteq R_{\text{inwork}}\) that satisfies unsafe criteria (3).

By that end, let

**OutSafetyBoxSet(R_{\text{inwork}}, j) = \{\text{shift}(R', -g^{(j)}) | \forall R' \in \text{shift}(R_{\text{inwork}}, g^{(j)}) \cap \text{SafetyBox}\}.**

It denotes the set of rectangles \(R''\) such that \(R'' \subseteq R_{\text{inwork}}\) and \(\text{shift}(R'', g^{(j)}) \subset \text{OutSafetyBox}\).

Let

**UnsafeSet(R_{\text{inwork}}, j) = \{\text{shift}(R', -g^{(j)}) | \forall R' \text{ s.t. } R' = \text{shift}(R_{\text{inwork}}, g^{(j)}) \cap R_{\text{unsafe}}, where R'_{\text{unsafe}} \in \text{UnsafeRectSet}, and R' \neq \emptyset\}**

It denotes the set of rectangles \(R''\) such that \(R'' \subseteq R_{\text{inwork}}\) and \(\text{shift}(R'', g^{(j)}) \subseteq R'_{\text{unsafe}}\), where \(R'_{\text{unsafe}}\) is a known unsafe rectangle.
So the set

\[
\text{SuspiciousSet}(R_{\text{inwork}}, j) = \text{OutSafetyBoxSet}(R_{\text{inwork}}, j) \cup \text{UnsafetySet}(R_{\text{inwork}}, j)
\]

is the set of rectangles \(\{R''\}\) containing all \(R'' \subseteq R_{\text{inwork}}\) and \(\text{shift}(R'', g^{(j)})\) is unsafe.

Let

\[
\text{SuspiciousSet}(R_{\text{inwork}}, j, j') = \bigcup_{R' \in \text{SuspiciousSet}(R_{\text{inwork}, j})} \text{SuspiciousSet}(R', j')
\]

It denotes the set of rectangles \(\{R''\}\) containing all \(R'' \subseteq R_{\text{inwork}}\), and \(\text{shift}(R'', g^{(j)})\) and \(\text{shift}(R'', g^{(j')})\) are both unsafe. Thus, we can compute the set \(\text{SuspiciousSet}(R_{\text{inwork}}, 0, 1, \ldots, n)\), which is the set of rectangles \(\{R''\}\) containing all \(R'' \subseteq R_{\text{inwork}}\) and \(\text{shift}(R'', g^{(j)})\) is unsafe for all \((0 \leq j \leq n)\). Therefore, \(\forall R_{\text{newUnsafe}} \in \text{SuspiciousSet}(R_{\text{inwork}}, 0, 1, 2, \ldots, n)\), \(R_{\text{newUnsafe}}\) satisfies the whole unsafety criteria. We thus attach them into the \(\text{UnsafeRectSet}\). Then starting with a \(R_{\text{newUnsafe}}\), repeat the process and find more unsafe rectangles. The process must terminate because \(\text{shift}(R_{\text{unsafe}}, g^{(j)})\) would shift the rectangle in at least \(n - 1\) positive directions. Finally the process must terminate when \(R_{\text{back}} = \emptyset\).

Fig. 5 shows an example illustrating how the algorithm works, although it may not correspond to any real 2D system. Algorithm 1, 2 and 3 show the pseudocode of our algorithm of constructing the \(\text{UnsafeRectSet}\). Once \(\text{UnsafeRectSet}\) is constructed, the \(\text{UnsafeRegion}\) is given by:

\[
\text{UnsafeRegion} = \bigcup_{R \in \text{UnsafeRectSet}} R
\]

**Algorithm 1** \text{construct UnsafeRectSet}

\[
\text{UnsafeRectSet} = \text{DeadRectSet}
\]

for \(R_{\text{dead}} \in \text{DeadRectSet}\) do
\[
\text{recur_sur}(R_{\text{dead}})
\]
end for

**Algorithm 2** \text{recur_sur}(R_{\text{unsafe}})

for \(i = 0\) to \(n\) do
\[
\text{s} = \text{sur}(R_{\text{unsafe}}, i)
\]
if \(s \neq \emptyset\) then
\[
\text{for } R \in s \text{ do}
\]
\[
\text{UnsafeRectSet.append}(R)
\]
\[
\text{recur_sur}(R)
\]
end for
end if
end for

**Algorithm 3** \text{sur}(R_{\text{unsafe}}, i)

\[
R_{\text{back}} = \text{shift}(R_{\text{unsafe}}, -g^{(i)}) \cap \text{SafetyBox}
\]

if \(R_{\text{back}} = \emptyset\) then
\[
\text{return } \emptyset
\]
end if

\[
\text{for } R_{\text{newUnsafe}} \in \text{UnsafeRectSet} \text{ do}
\]
\[
\text{workingSet} = \text{workingSet} \cup (R_{\text{back}} \setminus R_{\text{newUnsafe}})
\]
end for

for \(j = 0\) to \(n\) do
\[
\text{if } j = i \text{ then}
\]
continue
end if
\[
\text{newWorkingSet} = \emptyset
\]
\[
\text{for } R_{\text{inwork}} \in \text{workingSet} \text{ do}
\]
\[
\text{newWorkingSet} = \text{newWorkingSet} \cup \text{SuspiciousSet}(R_{\text{inwork}, j})
\]
end for
\[
\text{workingSet} = \text{newWorkingSet}
\]
end for
\[
\text{return } \text{workingSet}
\]

**B. Properties of UnsafeRegion**

**Lemma 4.** Any state in \(\text{UnsafeRegion}\) is infeasible.

**Proof:** By definition, \(\forall X \in \text{UnsafeRegion}, \exists R \in \text{UnsafeRectSet}, X \in R\). If \(R \in \text{DeadRectSet}\), then the system must fail in next time step. If \(R \notin \text{DeadRectSet}\), then from the unsafety criteria (3) \(\exists R' \in \text{UnsafeRectSet} \cap \text{SuspiciousSet}(R_{\text{inwork}}, 0, 1, 2, \ldots, n)\) such that \(\text{shift}(R, g^{(j)}) \subseteq R'\). Suppose in the process of constructing \(\text{UnsafeRectSet}\), we attach an incrementing ID to each rectangle added to the \(\text{UnsafeRectSet}\) starting from those rectangles in \(\text{DeadRectSet}\). Then \(R'\) must have a smaller ID than \(R\). So any states in \(R\) must fall into a rectangle that has a smaller ID than \(R\) or out of the safety box. Thus by induction those states must eventually reach one of the \(\text{DeadRects}\) or fail before that. In any case, those states will fail.

Let \(\text{SafeRegion} = \text{SafetyBox} \setminus \text{UnsafeRegion}\).

**Lemma 5.** Any state in \(\text{SafeRegion}\) is feasible.

**Proof:** \(\forall X \in \text{SafeRegion}\), since the state space is continuous, there must exist a rectangle \(R\) such that \(X \in R\). Then \(R\) must neither be in \(\text{UnsafeRectSet}\) nor a part of a rectangle that is in \(\text{UnsafeRectSet}\). So \(\exists j(0 \leq j \leq n), \text{shift}(R, g^{(j)}) \subseteq \text{SafeRegion}\). Thus \(X + g^{(j)} \in \text{SafeRegion}\). So by induction there is an infinite sequence \(g^{(0)}g^{(1)} \cdots\) such that \(X + g^{(j)} + g^{(j')} + \cdots \in \text{SafeRegion}\). Thus \(X\) is feasible.

**Theorem 3.** A system is feasible if and only if its initial state \(X(0) \in \text{SafeRegion}\).
Consider $R$ because they are already included in known unsafe rectangles. Three unsafe rectangles are found in $R$ a child the point is closer than its parent in at least $\lambda$. The search must terminate because every child rectangle other unsafe rectangles are found in the same fashion. The final result:

\[\text{SuspiciousSet}(R_{\text{inwork}}, 0) = \{ R_{\text{suspect}}^{0, 0}, R_{\text{suspect}}^{0, 1} \},\]

because $\text{OutSafetyBox}(R_{\text{inwork}}, 0) = \{ R_{\text{suspect}} \}$ and $\text{UnsafeSet}(R_{\text{inwork}}, 0) = \{ R_{\text{suspect}}^{0, 1} \}$.

\[\text{SuspiciousSet}(R_{\text{inwork}}, 0, 1, 2) = \{ R_{\text{suspect}}^{1, 0}, R_{\text{suspect}}^{1, 1}, R_{\text{suspect}}^{1, 2} \},\]

because $\text{OutSafetyBox}(R_{\text{inwork}}, 0, 1, 2) = \{ R_{\text{suspect}}^{0, 1} \}$ and $\text{UnsafeSet}(R_{\text{suspect}}^{1, 2}, 2) = \{ R_{\text{suspect}}^{1, 2} \}$

Figure 5. $R_{\text{unsafe}}, R_{\text{unsafe}}^2$ and $R_{\text{unsafe}}^3$ are known unsafe rectangles. Find more unsafe rectangles by examining $R_{\text{back}} = \text{shift}(R_{\text{unsafe}}, -g^{(i)}) \cap \text{SafetyBox}$. Two sub-rectangles of $R_{\text{back}}$ are put into the working set: $R_{\text{inwork}}^1$ and $R_{\text{inwork}}^2$, whereas others are discarded because they are already included in known unsafe rectangles. Three unsafe rectangles are found in $R_{\text{inwork}}^1$: $R_{\text{suspect}}^{0, 0}$, $R_{\text{suspect}}^{0, 1}$ and $R_{\text{suspect}}^{0, 2}$. Note that there are different ways of partitioning the space of $R_{\text{inwork}}^1 \cup R_{\text{inwork}}^2$ into a working set. However they are equivalent in producing the final result:

\[\bigcup_{R_{\text{inwork}}^1 \in \text{workingSet}} R_{\text{newUnsafe}} \subseteq \text{SuspiciousSet}(R_{\text{inwork}}, 0, 1, 2)\]

The recursive call of $\text{recur_sur}$ resembles a tree structure. From a rectangle $R_{\text{dead}}$, each $g^{(i)} (1 \leq i \leq n)$ may lead to a set of unsafe rectangles. From every one of these rectangles, other unsafe rectangles are found in the same fashion. The third case of 2D systems is a good example (Fig. 6), although in this case any finite set of unsafe rectangles returned by $\text{sur}$ call contains only one element.

Our algorithm performs a depth first search on the tree. The search must terminate because every child rectangle is closer than its parent in at least $n - 1$ directions to the point $[1 \ 1 \ \cdots \ 1]^T$ in the state space. Eventually, a child $R$ would be too close such that $\forall i (0 \leq i \leq n), \text{shift}(R, -g^{(i)}) \subseteq \text{OutSafetyBox}$. Consider the sum of the lower bounds of a rectangle $R$ in the tree in all directions. That is, for $R = [r_{10}, r_{11}] \times [r_{20}, r_{21}] \times \cdots \times [r_{n0}, r_{n1}]_n$, let $S = \sum_{i=1}^{n} r_{i0}$. Also let $\bar{b}_{\text{min}} = \min(\bar{b}_1, \bar{b}_2, \cdots, \bar{b}_n)$. From a parent to a child in the tree, $S$ is increased by at least $(n - 1)\bar{b}_{\text{min}}$. But $S < n$. So the height of the tree $\text{treeHeight} < \frac{n}{(n-1)\bar{b}_{\text{min}}}$. However the number of unsafe rectangles may be exponential to $n$. Note that from a parent to a child, the size of the rectangle must be decreasing. So there must be a rectangle of the smallest size $\lambda$. Since the length of the rectangle in every direction is less than 1, $\lambda$ is exponential to $-n$. The total number of unsafe rectangles $N$ is in the order of $\frac{1}{\lambda}$, thus $N$ is exponential to $n$. Indeed, if $\bar{b}_{\text{min}}$ is very small compared to 1, not only the tree could be tall but also the
that computes the next scheduling decision on the fly: \( \forall D. \) Scheduling policy

time to compute the SuspiciousSet \( O \) size formally.

bring a big performance issue to our algorithm. time is thus \( O \) may take \( O \) order of \( (g) \) search for \( \sum G \) time. By that end, the set of possible movements the situation where at most \( k \) ON at any time, our algorithm can be extended to deal with more complex tasks’ dynamics as well, for example those characterized by affine differential equations, which are considered in [2]. This extension is beyond the scope of this paper and will be addressed in future papers.

V. Simulation and Results

We perform simulations on different systems. Fig. 7 shows the results on some 2D and 3D systems. The rectangles in grey are the unsafe rectangles. Fig. 7a shows a 2D system that does not satisfy the necessary condition given by (7). All the states in the system are infeasible. The system in Fig. 7b just satisfies the necessary condition. It belongs to the third case of 2D systems we discussed. Fig. 7c shows a 2D system of the second case, while in Fig. 7d a system of the first case is shown. The system in Fig. 7e is not discussed because we assume \( \hat{a}_1 + \hat{b}_1 \leq 1 \) and \( \hat{a}_2 + \hat{b}_2 \leq 1 \) in order to get an analytical form of necessary and sufficient conditions. But our algorithm does not make any assumption on \( \{\hat{a}_i, \hat{b}_i\} \) thus it can correctly find the unsafe rectangles.

Fig. 7f shows an example of 3D systems that do not satisfy the necessary condition (6). All states are infeasible there. The system in Fig. 7g just satisfy the condition, so the system is feasible if and only if the initial state is not in the unsafe region, shown in gray in the figure. The algorithm suggests the safe region is the following:

\[
[0.0,0.15) \times [0.1,0.2) \times [0.4,1.0) \cup [0.15,0.3) \times [0.2,1.0) \times [0.0,1.0) \cup [0.0,0.15) \times [0.2,1.0) \times [0.0,1.0) \cup [0.0,0.15) \times [0.1,0.2) \times [0.4,1.0)
\]

VI. Related Work

As mentioned, [2] presents a necessary and sufficient condition in continuous time domain for any system to be feasible. However, when time is discretized additional conditions are required. [2] also mentions that systems in the intersection of two critical zones are infeasible but those infeasible regions are not complete. Other regions may also be infeasible. In this paper we present an algorithm to find all the infeasible regions for the discrete-time linear case.

Work has been done towards energy efficient CPU scheduling using Dynamic Voltage Scaling (DVS) and energy aware task allocation ([7], [8] and [9]). The integration of control and scheduling has been covered by [10], [11] and [12], where real-time scheduling approaches are extended to incorporate control task specifications. Our approach and the approach in [2], [3] is focused on energy consuming control systems with a system-wide resource constraint and departs from a CPU-centric view.
general and sufficient conditions for the system to be feasible. For more assumptions to hold, we can determine analytically the necessary green scheduling problem. For a system of two tasks, if certain (and not based on state feedback) makes the system overly assumption that electrical loads need to switch periodically the use of traditional scheduling algorithms but the underlying physical system. Although the periodic task model allows for and [4] by assuming a periodic task activation model for the EDF and RMS, for activation of electrical loads is used in [13] extension of traditional real time scheduling algorithms like to a PSU-centric (Power Supply Unit) resource allocation. The

![Figure 7. UnsafeRegion (in gray) of different systems.](image)

to a PSU-centric (Power Supply Unit) resource allocation. The extension of traditional real time scheduling algorithms like EDF and RMS, for activation of electrical loads is used in [13] and [4] by assuming a periodic task activation model for the physical system. Although the periodic task model allows for the use of traditional scheduling algorithms but the underlying assumption that electrical loads need to switch periodically (and not based on state feedback) makes the system overly constrained and less flexible to changes in system dynamics.

**VII. Conclusion**

We have studied the feasibility of the discrete-time linear green scheduling problem. For a system of two tasks, if certain assumptions hold, we can determine analytically the necessary and sufficient conditions for the system to be feasible. For more general n-dimensional systems, we design and implement an algorithm which, given the increasing and decreasing rates of the tasks of a system, returns a subset of the state space such that the system is feasible if and only if the initial state is in the subset. Given the subset, a scheduling policy can be computed on the fly as the system runs, with the flexibility to add any power-saving, priority based or fair sub-policies.

**REFERENCES**


