Abstract

We present a solution of a class of network utility maximization (NUM) problems using minimal communication. The constraints of the problem are inspired less by TCP-like congestion control but by problems in the area of internet of things and related areas in which the need arises to bring the behavior of a large group of agents to a social optimum. The approach uses only intermittent feedback, no inter-agent communication, and no common clock.

The proposed algorithm is a combination of the classical AIMD algorithm in conjunction with a simple probabilistic rule for the agents to respond to a capacity signal. This leads to a nonhomogeneous Markov chain and we show almost sure convergence of this chain to the social optimum.

Keywords: AIMD; Nonhomogeneous Markov Chains; Invariant Measure; Iterated Function Systems; Almost Sure Convergence; NUM with intermittent feedback

1 Introduction

Recent developments in the context of Smart Grid, Smart Transportation, and the internet have given rise to a rich set of optimization problems in which a number of agents collaborate to achieve a social optimum [10, 33, 15, 30, 12]. For example, collaborative cruise control systems are emerging in which a group of vehicles on a stretch of road share information to determine a speed limit that minimizes fuel consumption subject to some constraint (traffic flow, pollution constraints, etc.). Other examples of this problem can be found in several application domains; in the energy literature [41, 19, 4]; in the electric vehicles literature [21, 11, 18, 8], in distributed load control [30]; in the study of control strategies for thermostatically controlled loads, as refrigerators or air conditioners [1, 42, 35], and of course, in the optimization literature itself [10, 20].

Roughly speaking the optimization problems that emerge in such applications are simple to solve. Typically, one wishes to minimize a sum of strictly convex functions of a single variable subject to a linear, or perhaps, polynomial constraint. It is well known that such problems can be readily solved by a multitude of methods in a convex optimization framework [7]. Notwithstanding this fact, solving these problems in a smart grid or smart transportation framework is challenging. The difficulties that arise in such environments are due to several factors.

First one wishes to find solutions which can be implemented with minimal communication (or even none) between individual agents, and between the agents and infrastructure. This need arises due to the fact that many of these problems are massively large scale in nature, and continuous inter-agent communication would place an undue burden on the telecommunications infrastructure [30] and due to privacy...
The second difficulty is that the number of agents participating in the optimization problem is large and time-varying, and each agent’s utility is private and is not communicated to other agents in order to preserve this privacy. An additional further difficulty arises because agents in such applications typically have limited actuation capabilities, i.e. limited capabilities of effecting a change in their state. For example, in internet of things applications agents can often only influence their behavior by switching themselves on or off. Thus, distributed algorithms for solving large scale optimization problems in which agents with limited actuation capabilities collaborate to achieve a common goal, is a highly topical research problem.

Our objective in this paper is to develop algorithms that can be deployed in such situations. To this end, consider a network of \( n \) agents, each with a state \( x_i \in \mathbb{R}, i = 1, \ldots, n \) representing an amount of allocated resource. The allocated resource will be updated at discrete time instances \( k = 0, 1, 2, \ldots \), where in implementations a common clock is not required. The agents also keep track of their individual long term average \( \bar{x}_i(k) = \frac{1}{k+1} \sum_{j=0}^{k} x_i(j) \). (1)

We assume an upper bound \( C > 0 \) of the possible use of resources. To each agent we associate a cost function \( f_i : [0, C] \to \mathbb{R} \). We consider the problem of network-wide optimal allocation, which can be stated as

\[
\text{minimize}_{w_1, \ldots, w_n} \sum_{i=1}^{n} f_i(w_i) \\
\text{subject to} \quad \sum_{i=1}^{n} w_i = C, \quad w_i \geq 0, i = 1, \ldots, n.
\] (2)

Under suitable convexity assumption this optimization problem has a unique optimal point \( w^* \). We wish to steer the average values \( \bar{x}_i \) to the optimal point, i.e. we are looking for an algorithm such that

\[
\lim_{k \to \infty} \bar{x}_i(k) = w_i^*.
\]

Further, we wish to do this with as little inter-agent communication as possible, and with a minimum amount of centralized actuation. As we shall see inter-agent communication is not necessary at all to achieve convergence to the optimum, nor is it necessary to communicate a feedback signal in the form of a multiplier. Rather, we will show that it is sufficient to provide the centralized, one-bit information, that the constraint has been reached. Furthermore, the conditions for convergence are independent of network dimension, depending only on the worst agent in the system.

All this can be achieved using only the **additive-increase multiplicative decrease (AIMD)** algorithm. Recall that AIMD is an algorithm in which agents continuously claim more and more of the available resource in a gentle fashion until a notification (of a capacity event) is sent to them that the aggregate amount of available resource has been exceeded. This is the additive increase (AI) phase of the algorithm. They then reduce their demand on resource by a factor between zero and one. This is the multiplicative decrease (MD) of the algorithm. The AI phase of the algorithm then restarts immediately. In the algorithm each agent will respond to the capacity signal with a certain probability \( \lambda_i \). The key observation is that by choosing \( \lambda_i \) as a function of the long term average \( \bar{x}_i(k) \) we may achieve convergence to the optimal point \( w_i^* \) without any communication besides the capacity signal.

To motivate this result, we make use of the following two known observations.

**Observation 1 (Consensus)**: The optimization problem may be formulated in a Lagrangian framework as follows. We introduce the Lagrange parameter \( \mu \in \mathbb{R} \) and consider

\[
H(w_1, \ldots, w_n, \mu) = \sum_{i=1}^{n} f_i(w_i) - \mu \left( \sum_{i=1}^{n} w_i - C \right).
\] (3)
AIMD and Optimization

From the Karush-Kuhn-Tucker (KKT) conditions [7, Section 5.5.3], the following necessary and sufficient condition for optimality can be obtained by setting all partial derivatives to zero. If we assume that the optimal point $w^*$ has only positive entries, then the inequality constraints $w_i \geq 0$ are not active. In this case it is easy to see that the multipliers corresponding to the inequality constraints vanish in the KKT conditions. So under the assumption of positivity of the optimal point $w^* \in \mathbb{R}^n$, $\mu^* \in \mathbb{R}$ we have

$$\mu^* = \frac{\partial f_i}{\partial x_i}(w^*_i) \quad \forall \ i = 1, \ldots, n. \quad (4)$$

In other words, the system is at optimality when the derivatives of the utility functions are in consensus. We will show in Lemma [44] that the assumptions to be imposed for our algorithm imply that the optimal point is positive and so (4) does indeed characterize the optimal point.

**Observation 2 (Ergodic behavior):** It follows from the results in [43], under the assumptions of ergodicity, that the ergodic limit of a network of AIMD flows is almost surely of the form

$$\lim_{k \to \infty} \frac{1}{k + 1} \sum_{j=0}^k x_i(j) = \frac{\Theta}{\lambda_i}, \quad (5)$$

where $\Theta$ is a network-specific constant and $\lambda_i$ is the steady-state probability that the $i$th AIMD agent responds to a notification of a capacity event.

With these two observations in mind, we can now aim to choose place-dependent probability functions $\lambda_i(\cdot)$ so that the equation for the steady state behavior (5) is equivalent to the KKT condition (4).

Suppose that, in the $k$th iteration, each agent responds to a capacity event with probability

$$\lambda_i(\bar{x}_i(k)) = \Gamma \frac{f'_i(\bar{x}_i(k))}{\bar{x}_i(k)}, \quad (6)$$

where $\bar{x}_i(k)$ is the average of the last $k$ values of $x_i$. Here $\Gamma$ is a network wide constant chosen to ensure that $0 < \lambda_i(\bar{x}_i) < 1$. Suppose now that $\bar{x}_i(k) \approx x_i^*$. Then we can write $\lambda_i(\bar{x}_i(k)) \approx \lambda_i^*$. Provided that for this choice (5) holds, we obtain for large $k$

$$\lambda_i(\bar{x}_i(k)) \approx \Gamma \frac{f'_i(\bar{x}_i(k))}{\Theta} \lambda_i(\bar{x}_i(k)) \quad (7)$$

and so $f'_i(\bar{x}_i(k)) \approx \Theta/\Gamma \approx f'_j(\bar{x}_j(k))$ for all $i, j$. These are precisely the KKT conditions which in many cases are both necessary and sufficient for optimality.

The purpose of this paper is to show that the above intuition is true. Specifically, with the place-dependent probabilities $\lambda_i(\cdot)$ chosen as in (6), we do indeed have $\bar{x}_i(k) \approx x_i^*$ for large $k$. Consequently, the AIMD algorithm can be modified to solve distributed optimization problems in asynchronous environments in a manner that is both effective and efficient in terms of communication overhead.

Our paper is structured as follows. We begin by reviewing a recently proposed switched systems model of AIMD dynamics and known results on the stochastic stability of this model for fixed probabilities. The main result for fixed probabilities is that the long term averages converge almost surely and that this limit can be expressed analytically. We start in Section 2 by introducing notation and recalling some facts about the dynamics of stochastic AIMD algorithms. In Section 3 we present a discussion of a stochastic AIMD algorithm that solves the NUM problem. In Section 4 we introduce two dynamical systems, representing these algorithms. These differ in the choice of the probability laws. We then state the main convergence results. Related works are discussed in Section 5. In Section 6 we apply the results to solve the NUM problem for a network of agents. The main proofs are provided in the Appendix. There, we give intermediate results that link the fixed probability case with the place-dependent case. Specifically, we ask to what degree may the place dependent case be approximated with the fixed probability case, and over which time intervals. To this end we study the robustness properties of a deterministic system that iterates on the expectation operator. These results are then used to establish the main result of the paper.
Remark 1.1 The main contribution of this paper is to propose a new technique for solving a NUM problem that can be used in IoT related situations. Various techniques exist for solving such problems and we shall enunciate the difference of our method, with respect to these, in the related work section later in the paper. However, since AIMD is so closely related to Transmission Control Protocol (TCP), and since TCP can be studied in an optimization framework, several brief comments are merited at this point to avoid any confusion. First, we do not account for queues in the network, nor do we assume that these give rise to a loss process. Also, we do not use ODE’s, or fluid like approximations, to model our network. Rather, we study an exact discrete time system that arises in the study of AIMD dynamics, without queues, in which losses are governed agents themselves in the network. In other words, and in the language of TCP, in our setting losses are generated at the edge, unlike most TCP systems, in which losses are generated at the center via queuing dynamics. Our principal concern is to determine rules by which agents generate these losses so that certain optimization problems can be solved. All together, this gives rise to a “Markov-like” system which requires special machinery for its study, and a large part of this paper is devoted to developing this machinery.

2 Preliminaries

Our starting point is the suite of algorithms that underpin the Transmission Control Protocol (TCP) that is used in internet congestion control. A fundamental building block of TCP is the Additive Increase Multiplicative Decrease (AIMD) algorithm. To discuss AIMD in a formal setting some preliminaries are necessary.

2.1 Notation:

The vector space of real column vectors with \( n \) entries is denoted by \( \mathbb{R}^n \) with elements \( x = [x_1 \ldots x_n]^\top \), where \( x^\top \) denotes the transpose of \( x \). The positive orthant \( \mathbb{R}^n_+ \) is the set of vectors in \( \mathbb{R}^n \) with non-negative coordinates. For \( x, y \in \mathbb{R}^n \), we write \( x \gg y \) if \( x_i > y_i \) for all \( i = 1, \ldots, n \). The space of \( n \times n \) matrices is denoted by \( \mathbb{R}^{n \times n} \) and \( \mathbb{R}^{n \times n}_+ \) is the set of non-negative matrices, i.e. the set of matrices in which all entries are non-negative. The convex hull of a set \( X \) is denoted by \( \text{conv} X \); it may be defined as the smallest convex set containing \( X \).

We denote the canonical basis vectors in \( \mathbb{R}^n \) by \( e_i, i = 1, \ldots, n \) and let \( e := \sum_{i=1}^n e_i \). The standard 1-norm is defined by \( \|x\|_1 = \sum_{i=1}^n |x_i|, \) \( x \in \mathbb{R}^n \). The closed ball of radius \( \delta \) around 0 with respect to this norm is denoted by \( B_1(0, \delta) \). The distance of a point \( x \) to a nonempty set \( Z \) with respect to the 1-norm is then

\[
\text{dist}_1(x, Z) := \inf \{\|x - z\|_1 ; z \in Z\}.
\]

The standard simplex \( \Sigma \) in \( \mathbb{R}^n \) is defined by

\[
\Sigma := \left\{ x \in \mathbb{R}^n_+ \mid \sum_{i=1}^n x_i = 1 \right\}.
\]

We will write \( \Sigma_n \) if we want to emphasize that we are working in \( \mathbb{R}^n \). Note that we are only interested in dynamics on \( \Sigma \). Thus when we write \( B_1(0, \delta) \) we will tacitly assume that we consider the intersection of this ball with \( \Sigma \). The relative interior of \( \Sigma \) is defined by \( \text{ri} \Sigma := \{ x \in \Sigma \mid x_i > 0, i = 1, \ldots, n \} \). It will be sometimes useful to use the Hilbert metric \( d_H(\cdot, \cdot) \) on \( \text{ri} \Sigma \). Recall that it is given by

\[
d_H(x, y) := \max_i \log(x_i/y_i) - \min_j \log(x_j/y_j), \quad x, y \in \text{ri} \Sigma,
\]

and makes \( (\text{ri} \Sigma, d_H) \) a complete metric space. A ball of radius \( \delta \) with respect to the Hilbert metric is denoted by \( B_H(x, \delta) \); again without further notice, we will understand that \( B_H(x, \delta) \) is the ball contained in \( \Sigma \). For the sake of analysis, it is sometimes easier to work with the logarithm removed, in which case we consider

\[
e^{\delta_H}(x, y) := \frac{\max_i x_i/y_i}{\min_j x_j/y_j}, \quad x, y \in \text{ri} \Sigma.
\]
Note that for $x_k, x, y, z \in \Sigma$ we have $\|x_k - y\|_1 \to 0$ if and only if $d_H(x_k, y) \to 0$ which is in turn equivalent to $e^{d_H}(x_k, y) \to 1$. Furthermore, $d_H(x, y) < d_H(z, y)$ if and only if $e^{d_H}(x, y) < e^{d_H}(z, y)$.

### 2.2 AIMD algorithms and stochastic matrices

We have already mentioned that the AIMD algorithm underpins TCP. We shall not describe the TCP algorithm here. Rather, we refer the interested reader to \cite{31,32,15,14} for details of TCP. The dynamics of networks of AIMD flows can be described as

$$x(k + 1) = A(k)x(k),$$

where $A(k)$ is a non-negative column stochastic matrix and $k$ enumerates the capacity events. The matrices $A(k)$ belong to a finite set of matrices $A$, which we now describe. Given two vectors $\alpha \in \Sigma, \beta \in (0, 1)^n$ we define a set $A$ of $2^n$ matrices as follows. Let

$$B := \\{ \tilde{\beta} \in \mathbb{R}^n \mid \tilde{\beta}_1 \in \{\beta, 1\} , \ i = 1, \ldots, n \},$$

which is clearly a set with $2^n$ elements. The set of AIMD matrices is then given by

$$A := \\{ \text{diag}(\tilde{\beta}) + \alpha(e - \tilde{\beta})^\top \mid \tilde{\beta} \in B \}.$$  

Note that $\alpha(e - \tilde{\beta})^\top \in \mathbb{R}^{n \times n}$ as $\alpha \in \mathbb{R}^{n \times 1}$ and $(e - \tilde{\beta})^\top \in \mathbb{R}^{1 \times n}$. Such matrix sets and the dynamics of Markov chains on $\Sigma$ defined by $A$ have been studied in \cite{49,43,12}. We single out the matrix for which all diagonal entries are below unity and use the convention that the matrix $A_1 \in A$ is defined using $\beta$, that is,

$$A_1 = \text{diag}(\beta) + \alpha(e - \beta)^\top.$$  

Note that $A_1$ is a column stochastic, positive matrix. In particular, $\lambda = 1$ is a simple eigenvalue of $A_1$ and it is larger in magnitude than all the other eigenvalues of $A_1$ by the Perron-Frobenius theorem. It is easy to see that a corresponding positive eigenvector is

$$z = \left[ \begin{array}{ccc} \frac{\alpha_1}{1 - \beta_1} & \cdots & \frac{\alpha_n}{1 - \beta_n} \end{array} \right]^\top.$$  

AIMD matrices have the property that they leave the subspace

$$V := \{ x \in \mathbb{R}^n \mid e^\top x = 0 \}$$

invariant, as they are column stochastic. Finally, we recall the following fact about the contractive properties of $A_1$ from \cite{49,12}. In the following statement $A_1|_V$ denotes the restriction of $A \in A$ to the invariant subspace $V$.

**Lemma 2.1** Let $\alpha \in \Sigma, \beta \in (0, 1)^n$ and let $A$ be the corresponding set of AIMD matrices. Then for all $A \in A$ we have $\|A_1|_V\|_1 \leq 1$. Also there exists a constant $c \in (0, 1)$ such that for the matrix $A_1$ defined by \cite{10} we have

$$\|A_1|_V\|_1 = c < 1.$$  

### 2.3 Elementary results on AIMD

The AIMD algorithm is often studied under the assumption that probabilities are not place-dependent; namely, the probability that $A(k) = A \in A$ is independent of $k$ and $x(k)$. It shall be useful to refer to this case in the remainder of the paper and we briefly recall relevant known results here. Consider a probability distribution $p : A \to [0, 1], A \mapsto p_A$ on the set $A$ of AIMD matrices. This induces a Markov chain on $\Sigma$ by setting

$$x(k + 1) = A(k)x(k), \quad k \in \mathbb{N}, \quad x(0) = x_0 \in \Sigma,$$  

where $P(A(k) = A) = p_A$ for $A \in A$. In particular, the sequence of transition matrices $\{A(k)\}$ is IID. In the sequel, we will consider the case in which the probabilities $p_A$ are derived from individual drop
probabilities \( \lambda_i \) of the agents. In this case, \( \lambda_i \) is the probability that in \( i \) we have \( \tilde{\beta}_i = \beta_i \). In this case, for every \( \tilde{\beta} \in B \), or equivalently \( A \in A \), we have
\[
P\left( A(k) = \text{diag}(\tilde{\beta}) + \alpha(e - \tilde{\beta})^\top \right) = \prod_{\tilde{\beta}_i = \beta_i} \lambda_i \prod_{\tilde{\beta}_i = 1} (1 - \lambda_i) .
\] (13)

For the Markov process defined by (12) it is known from the results in [49, 43, 12] that if \( \lambda = [\lambda_1 \ldots \lambda_n] \gg 0 \), then there is a unique, invariant, probability measure \( \pi \) on \( \Sigma \) for the Markov chain. We denote by \( \hat{\mathbb{P}}_\lambda \) the probability measure induced on the sample space by the assumption of the IID probabilities \( \lambda \). Then, for every initial state \( x_0 \in \Sigma \), we have
\[
\lim_{k \to \infty} \hat{x}(k) = \xi_\lambda , \quad \hat{\mathbb{P}}_\lambda - \text{almost surely},
\] (14)

where
\[
\hat{x}(k) := \frac{1}{k+1} \sum_{j=0}^k x(j)
\] (15)

and
\[
\xi_\lambda := \frac{1}{\sum_{i=1}^n \alpha_i} \left[ \begin{array}{c} \alpha_1 \\ \lambda_1(1 - \beta_1) \\ \vdots \\ \alpha_n \\ \lambda_n(1 - \beta_n) \end{array} \right] ^\top .
\] (16)

As almost sure convergence implies convergence in probability this shows that for every \( x_0 \in \Sigma \) and \( \varepsilon, \delta > 0 \) there exists a \( k_0 \) such that for all \( k \geq k_0 \) we have
\[
\mathbb{P}_\lambda (||\hat{x}(k;x_0) - \xi_\lambda||_1 > \delta) < \varepsilon .
\] (17)

It will also be useful to have a uniform version of (17). To this end we define the random matrix
\[
\tilde{S}(k) := \frac{1}{k+1} \sum_{j=0}^k A(j-1) \cdots A(0) ,
\] (18)

with the interpretation that the summand corresponding to \( k = 0 \) is the identity \( I_n \). Our interest in this expression lies in the observation that for any initial condition \( x(0) = x_0 \in \Sigma \) we have
\[
\hat{x}(k;x_0) = \tilde{S}(k)x_0 ;
\] (19)

hence
\[
\hat{x}(k) - \xi_\lambda = (\tilde{S}(k) - \xi_\lambda e^\top)x_0 .
\] (20)

Lemma 2.2 Consider the random sequence \( \{\tilde{S}(k)\}_{k \in \mathbb{N}} \) given by (18) where \( \{A(k)\} \) is IID with probabilities given by (13). Then for every \( \varepsilon, \delta > 0 \) there exists a \( k_0 \in \mathbb{N} \) such that
\[
\mathbb{P}_\lambda (||\tilde{S}(k) - \xi_\lambda e^\top||_1 > \delta) < \varepsilon
\] (21)

for all \( k \geq k_0 \). Hence, considering the corresponding Markov chain (12), there exists a \( k_0 \in \mathbb{N} \) such that for all \( x_0 \in \Sigma \) and all \( k \geq k_0 \)
\[
\mathbb{P}_\lambda (||\tilde{x}(k;x_0) - \xi_\lambda||_1 > \delta) < \varepsilon .
\] (22)

Proof As \( \Sigma \) contains the canonical basis vectors \( e_i \), and the norm on \( \mathbb{R}^{n \times n} \) induced by \( || \cdot ||_1 \) is the max column sum norm, it follows that for all \( M \in \mathbb{R}^{n \times n} \)
\[
||M||_1 = \max_{i=1 \ldots n} ||Me_i||_1 = \max\{||Mx||_1 \mid x \in \Sigma \} .
\] (23)

Fix \( \varepsilon, \delta > 0 \). By (17) and in view of (20), we may choose for each \( i \) an integer \( k_i \) such that for all \( k \geq k_i \) we have
\[
\mathbb{P}_\lambda (||\tilde{S}(k) - \xi_\lambda e^\top||e_i|| > \delta) < \frac{\varepsilon}{n} .
\]

By choosing \( k_0 := \max\{k_1, \ldots, k_n\} \) we thus obtain for all \( k \geq k_0 \) that
\[
\mathbb{P}_\lambda (||\tilde{S}(k) - \xi_\lambda e^\top||_1 > \delta) = \mathbb{P}_\lambda \left( \max_{i=1 \ldots n} ||\tilde{S}(k) - \xi_\lambda e^\top||e_i|| > \delta \right) < \varepsilon ,
\] (24)

where we have used the standard estimate \( \mathbb{P}_\lambda (\cup_{i=1}^n W_i) \leq \sum_{i=1}^n \mathbb{P}_\lambda (W_i) \) for events \( W_i \). The claim is now an immediate consequence of (23).
2.4 Some comments on stochastic convergence

The main result of this paper yields conditions for almost sure convergence of the sample paths of a Markov chain. For the benefit of the reader we briefly point to relevant parts of the literature, where this notion is discussed. Readers familiar with notions of stochastic convergence may skip this section.

Given a Markov chain and an initial condition, we can consider the set of all possible sample paths \( \{ x(k;x_0,\omega) \mid \omega \in \Omega \} \), where \( \Omega \) is an index set for the set of different sample paths or trajectories of the Markov chain. In our case, the set \( \Omega \) can be identified with the set of all sequences with values in \( \{1,\ldots,2^n\} \), which can be interpreted as the set of sequences \( \{A(0),A(1),\ldots\} \) that lead to a particular sample path. Kolmogorov’s existence theorem now states that the marginal probabilities that are induced by the Markov chain on finite-time intervals define a probability measure \( P_\Omega \) on \( \Omega \), the set of sample paths, see [5, Sections 2, 24, 36].

The statement that convergence to a limit happens almost surely, thus means that the measure of the set of sample paths which are converging is 1; with respect to the probability measure \( P_\Omega \) on the sample space. Thus almost sure convergence means that the convergence happens with probability one, with the right interpretation of the probability measure.

It is furthermore known, that almost sure convergence implies convergence in probability, [5]. The latter concept is implicitly defined in (22): for every \( \varepsilon > 0 \) and \( \delta > 0 \) there exists a \( k_0 \) such that for all \( k \geq k_0 \) the probability of being further away from the limit than \( \delta \) is smaller than \( \varepsilon \).

3 AIMD Based Optimization Algorithm

In this section, we formally define the class of distributed optimization problems that can be addressed using the algorithm presented in this paper. Recall: let \( n \in \mathbb{N}, C > 0 \) and \( f_i : [0,C] \to \mathbb{R} \) be strictly convex and continuously differentiable, \( i = 1,\ldots,n \) and consider the optimization problem

\[
\begin{align*}
\text{minimize} & \quad \sum_{i=1}^{n} f_i(\bar{x}_i) \\
\text{subject to} & \quad \sum_{i=1}^{n} \bar{x}_i = C, \quad \bar{x}_i \geq 0.
\end{align*}
\] (25)

We are interested in finding the optimal point \( x^* \) in which the minimum is achieved. It is well-known that by compactness of the feasible space an optimal solution exists; it is unique by the assumption of strict convexity. We now formulate conditions guaranteeing that the unique, optimal point \( x^* \) is characterized by the existence of a constant \( \mu^* \in \mathbb{R} \) such that

\[
\sum_{i=1}^{n} x_i^* = C, \quad x_i^* \geq 0, \quad f_i'(x_i^*) = \mu^*, \quad i = 1,\ldots,n.
\] (26)

These conditions are such that the algorithm which we have briefly motivated can be implemented.

Lemma 3.1 Let \( n \in \mathbb{N}, C > 0 \) and \( f_i : [0,C] \to \mathbb{R} \) be strictly convex and continuously differentiable, \( i = 1,\ldots,n \). Assume that there exists a constant \( \Gamma > 0 \) such that for all \( x \in [0,C] \) and all \( i = 1,\ldots,n \) we have

\[
0 \leq \Gamma \frac{f_i'(x)}{x} \leq 1,
\] (27)

where for \( x = 0 \) the condition (27) is supposed to hold for the continuous extension of the middle term in \( x = 0 \). Then

(i) There exists a unique optimal point \( x^* \) for the minimization problem (25).

(ii) The optimal point \( x^* \) is positive, i.e. all its entries are strictly positive.

(iii) The optimal point is characterized by the simplified KKT conditions (26).
AIMD and Optimization

Proof (i) This is an immediate consequence of compactness of the feasible set and strict convexity of the cost function.

(ii) By strict convexity of the $f_i$, the derivatives $f_i'$ are strictly increasing. Also (27) implies that $f_i'(0) = 0$ for all $i = 1, \ldots, n$ as otherwise $f_i(x)/x$ could not be continuously extended to $x = 0$.

Let $x_0 = [x_{0,1} \ldots x_{0,n}]$ be a point on the relative boundary of the simplex $\Sigma_n$, i.e., such that one of its entries equals 0. Choose indices $j, \ell$ such that $x_{0,j} = 0, x_{0,\ell} > 0$. Denote

$$x_\varepsilon := [x_{\varepsilon,1} \ldots x_{\varepsilon,n}] := x_0 + \varepsilon e_j - \varepsilon e_\ell.$$

Clearly, $x_\varepsilon$ satisfies all constraints of (25) provided $\varepsilon > 0$ is small enough. We claim that for $\varepsilon > 0$ sufficiently small we have $\sum_{i=1}^n f_i(x_{\varepsilon,i}) < \sum_{i=1}^n f_i(x_{0,i})$, which shows that $x_0$ is not an optimal point. To prove the claim consider the derivative of the total cost with respect to $\varepsilon$ at $\varepsilon = 0$. We have

$$\frac{d}{d\varepsilon} \sum_{i=1}^n f_i(x_{\varepsilon,i}) = f_j'(0) - f_\ell'(0) = -f_j'(0) < 0,$$

where we have used that $f_j'$ is strictly increasing. It follows that $x_0$ is not an optimal point for the optimization problem (25). As $x_0$ was arbitrary on the relative boundary of the simplex this proves the assertion.

(iii) It follows from (ii) that the optimal point $x^*$ for problem (25) is also an optimal point for the optimization problem

$$\text{minimize} \sum_{i=1}^n f_i(\bar{x}_i)$$

subject to

$$\sum_{i=1}^n \bar{x}_i = C, \quad 0 < \bar{x}_i < C.$$

As the latter optimization problem is defined on an open subset of the affine space given by the constraint $\sum_{i=1}^n \bar{x}_i = C$, it follows that an optimal point, if it exists, satisfies the standard Lagrange optimality conditions. As we have seen in [4, 5], these simplify to the conditions stated in (26).

The implementation of the algorithm uses the current state of the users at a given time instance $t$, which we denote by $x_i(t)$ and the long-term average of the states of the users denoted by $\bar{x}_i(t)$. It is the aim of the algorithm to obtain convergence of the long-term averages to the KKT point $x^*$.

Furthermore, the actual algorithm implemented on each agent is based on the following assumptions.

We assume that agents can infer when $\sum_{i=1}^n x_i \geq C$. If this is not the case we assume that each agent is informed of a constraint violation at the instant of its occurrence using binary feedback. This is a capacity event notification. Upon receipt of such a notification agent $i$ updates the state $x_i(t)$:

$$x_i(t^+) = \beta x_i(t^-)$$

with probability

$$\lambda_i(\bar{x}_i(t^-)) = \Gamma \frac{f_j'(\bar{x}_i(t^-))}{\bar{x}_i(t^-)} \quad (30)$$

Note that in this definition we implicitly assume that the assumptions of Lemma 3.1 are met. In particular, there exists a constant $\Gamma > 0$ such that $\lambda_i(\bar{x}_i) \in [0,1]$ for all values $\bar{x}_i \in [0,C]$. This restricts the admissible choices for the cost functions $f_i$. We will discuss different ways of treating more general functions in Remark 3.3.

At all other time instants the rate of change of $\dot{x}_i(t)$ is chosen to be a positive quantity. Note that the superscripts $+$ and $-$ denote the instants immediately prior and after a capacity event notification, respectively. This leads to the following discrete time algorithm that is implemented on each of the agents. We assume a common time step $h$ is fixed and each agent $i$ has an internal offset $T_i$. For the sake of abbreviation, we denote $k_i := T_i + kh, k \in \mathbb{N}$ and $x_i(k_i) := x_i(T_i + kh)$.

---

2This is the intermittent feedback and the limited communication referred to throughout the paper.
Each agent sets its state \( x_i(0) \) to an arbitrary value.

The parameter \( \Gamma \) is broadcast;

\textbf{while} agent \( i \) is active \textbf{do}

\textbf{if} \( \sum_{i=1}^{n} x_i(k_i) < C \) \textbf{then}

\[ x_i((k+1)_i) = x_i(k_i) + \alpha \]

\textbf{else}

\[ x_i((k+1)_i) = \beta x_i(k_i) \text{ with probability } \lambda_i(x_i(k_i)) = \Gamma \frac{f_i(x_i(k_i))}{\bar{x}_i(k_i)} \]

\[ x_i((k+1)_i) = x_i(k_i) + \alpha \text{ otherwise}; \]

\textbf{end}

\textbf{end}

\textbf{Algorithm 1:} AIMD algorithm run by each agent

It is clear that the performance of the algorithm depends crucially on a number of assumptions. For example, we have assumed that the time between sample points is the same for all agents (note that a common clock is not necessary). Also the algorithm is implemented in discrete time, while the AIMD model we analyze has an implicit continuity assumption. This discrepancy requires that the sample times \( h \) are sufficiently small, when compared to \( C \) and \( n \). We will tacitly assume that the modeling error due to discretization effect is sufficiently small. A few further comments are required.

\textbf{Remark 3.2} The constant \( \Gamma \) is chosen to ensure that each \( \lambda_i(\bar{x}_i) \in (0, 1) \). Thus \( \Gamma \) depends on the worst utility function and must be communicated to all agents prior to the algorithms use. It is a network dependent quantity that is independent of network dimension.

We now briefly discuss how to reformulate NUM problems so that they satisfy the assumptions of our set-up. Note that the following list is not exhaustive.

\textbf{Remark 3.3} While the assumption that \( \lambda_i(r) \) is well defined and in \([0, 1]\) for all \( r \in [0, C] \) might sound restrictive for the problem at hand, we note that the following modifications of the problem yield a feasible solution.

(i) In case the objective functions are not increasing, we can define the constant

\[ q := \max_{i=1,...,n} |f'_i(0)| \]

and consider the objective functions \( \tilde{f}_i \), given by \( \tilde{f}_i(r) = f_i(r) + qr, r \in [0, C] \), which are now strictly increasing. Note that this does not change the KKT point, as \( \tilde{f}_i \equiv f'_i + q \), so that the condition that all derivatives are equal is met at the same point \( x \).

(ii) A second concern is that even if \( f'_i \geq 0 \) on \([0, C]\), the expression \( f_i(r)/r \) might tend to \( \infty \) as \( r \to 0 \), depending on the nature of the derivative of \( f_i \) at 0. In this case we may replace \( (30) \) with

\[ \tilde{\lambda}_i(r) := \min \left\{ 1, \Gamma \frac{f_i(r)}{r} \right\}, \quad r \in [0, C]. \]

This amounts to a regularization of the optimization problem which we briefly outline in a simple situation. Assume that there is a unique point \( r_T \in [0, C] \) such that \( r_T = \Gamma f'(r_T) \). If \( \lambda_i \) in \( (31) \) were the result of the definition in \( (30) \), the corresponding objective function would be

\[ \tilde{f}_i(r) := \begin{cases} f_i(r) - \frac{1}{2}r^2 \Gamma f''(r_T) & r \in [0, r_T] \\ f_i(r) + \frac{1}{2}r^2 \Gamma f''(r) & r \in [r_T, 1] \end{cases}, \quad r \in [0, C]. \]

More generally, there could be several interlacing intervals, in which the condition \( r_T < \Gamma f'(r_T) \) is satisfied or not. The important point here is that a decrease of \( \Gamma \) leads to a decrease of \( r_T \), so that by choosing \( \Gamma \) small enough, the KKT point of the original problem will be found by the algorithm.

We note that although our analysis will be performed for a fixed number of agents, this is not necessary in the implementation of the algorithm. Indeed, as no information is required on the number of agents, these may join or drop out of the network at any time and the network will automatically readjust the KKT point given the new set of agents.
4 Convergence Analysis

In this section we discuss two versions of the stochastic algorithm for the approximation of the KKT point $x^*$. The common feature of these algorithms is that the probabilities for backing off depend on an average of past states. In the first version, we assume that there is a fixed window over which the average is taken, while in the second case the average is taken over the complete history starting at time $t_0 = 0$.

The two approaches are amenable to different methods of analysis. In the first case the problem may be recast in terms of a homogeneous Markov chain with state-dependent probabilities, sometimes also called an iterated function system (IFS). In this setting classical results ensure the existence of an attractive invariant measure and ergodicity results follow. However, the real convergence result of interest can be proved for the second algorithm which only gives rise to a nonhomogeneous Markov chain and for which the powerful methods that exist for the first case are not available. The method of proof relies here on a detailed analysis of the system dynamics using appropriate Lyapunov functions.

For convenience, we will assume $C = 1$ in the remainder of the paper. We consider a set of AIMD matrices for fixed additive increase parameter $\alpha > 0$ and multiplicative decrease parameter $\beta \in (0, 1)$. We will assume there are probability functions $\lambda_i : \mathbb{R} \to \mathbb{R}, i = 1, \ldots, n$ that are used by each agent to determine the probability of responding to the intermittent feedback signal, based on an average of past values of $x$. We assume that these functions $\lambda_i : \mathbb{R} \to \mathbb{R}, i = 1, \ldots, n$ satisfy the following assumptions

(A1) $\lambda_i$ is continuous, $i = 1, \ldots, n$;
(A2) $r \mapsto r \lambda_i(r)$ is strictly increasing on $[0, 1], i = 1, \ldots, n$;
(A3) There exists a constant $\lambda_{\text{min}}$ such that $\lambda_i(r) \geq \lambda_{\text{min}} > 0$ for all $r \in [0, 1], i = 1, \ldots, n$;

Note that these assumptions are satisfied for the choice of probability functions described in Section 3. In particular, (A2) is a consequence of convexity. \[ We will show in Lemma B.1 that under the above conditions there is a unique KKT point $x^* \in \Sigma$. \]

It is discussed in [44, 49] that the dynamics of an algorithm of the type of Algorithm 1 can be well approximated by a Markov chain of AIMD matrices. In fact, if we let $k = 0, 1, 2, \ldots$ be the consecutive labels of the time instances at which the constraint is met, then the evolution from one constraint event to the next is given by (34) below, where $A(k)$ is one of the AIMD matrices describing the problem. Note that the probabilities $p_A(\cdot)$ for the matrices $A \in A$ are now determined by the assumption that the agents act in a stochastically independent manner, so that the probability of a particular drop pattern encoded in $A \in A$ is given by the product of the probabilities of the individual agents responding or not.

The system of interest is given by the iteration of AIMD matrices in the form

$$x(k + 1) = A(k)x(k), \quad (34)$$

where the matrices $A(k)$ are chosen from the set of AIMD matrices $A$ using a probability distribution that depends on the history of the sample path. Specifically, we consider the following two cases:

(i) **finite averaging:** We consider a fixed time window of length $T$. For $k \geq T - 1$ consider the average

$$\bar{x}_T(k) := \frac{1}{T} \sum_{j=0}^{T-1} x(k - j) \quad (35)$$

\[ The formulation can be extended using the same arguments to the assumption that the AIMD parameters of the agents are chosen such that $\alpha \in r \Sigma, \beta \in (0, 1)^n$ satisfy the added assumption that the quotient $\alpha_i/(1 - \beta_i)$ is a constant independent of $i$. \]
and suppose that there are probability functions \( p_A : \Sigma \to [0, 1], A \in \mathcal{A} \) such that
\[
P(A(k) = A) = p_A(\bar{x}_T(k)).
\] (36)

(i) **long-term averaging:** In this situation, we consider the average
\[
\bar{x}(k) := \frac{1}{k+1} \sum_{j=0}^k x(j)
\] (37)
for \( k = 0, 1, \ldots \) and suppose that there are probability functions \( p_A : \Sigma \to [0, 1], A \in \mathcal{A} \) such that
\[
P(A(k) = A) = p_A(\bar{x}(k)).
\] (38)

### 4.1 Finite Averaging

The condition (36) needs to be interpreted along sample paths: for each specific realization of the Markov chain, the probabilities at time \( k \) are a function of the average over the time interval \([k - T + 1, \ldots, k]\) for the given realization. We will model this Markov chain as a Markov chain with state-dependent probabilities on the space \( \Sigma^T \). In view of the evolution (34) with (35), (36), define the new variable
\[
z(k) := \left[ x(k) \quad \frac{1}{T}(x(k) + x(k - 1)) \quad \cdots \quad \frac{1}{T}(x(k) + \cdots + x(k - T + 1)) \right]^\top.
\] (39)

It is then easy to see that the evolution of \( z(k) \) is described by the Markov chain
\[
z(k+1) = \begin{bmatrix}
A(k) & 0 & \ldots & 0 \\
\frac{1}{T} (A(k) + I) & 0 & \ldots & 0 \\
\frac{1}{T} A(k) & \frac{2}{T} I & 0 & \ldots & 0 \\
& \ddots & \ddots & \ddots & \ddots \\
& & & \frac{1}{T} A(k) & 0 & \ldots & 0 & \frac{T-1}{T} I & 0
\end{bmatrix} z(k) := A_T(k)z(k).
\] (40)

Given \( A \in \mathcal{A} \), we denote by \( A_T \in \mathbb{R}^{Tn \times Tn} \) the matrix obtained from \( A \) through the construction in (40). Note that each matrix \( A \in \mathcal{A} \) uniquely defines a matrix \( A_T \) and the set of possible matrices \( \mathcal{A}_T \) occurring in the Markov chain (40) is defined in this way. The Markov chain is thus defined with the place-dependent probabilities
\[
P(A_T(k) = A_T) = p_A(z_T(k)),
\] (41)
where \( A \in \mathcal{A} \) and where \( z_T(k) \in \Sigma \) denotes the \( T \)th component vector of \( z(k) \). The following norm on \( \mathbb{R}^{Tn} \) simplifies the analysis of the Markov chain considerably, as it reveals its contractive properties. We define
\[
\|z\|_T := \max_{i=1,\ldots,T} \|z_i\|_1, \quad \text{where} \quad z = [z_1^\top \ldots z_T^\top]^\top, z_i \in \mathbb{R}^n, i = 1, \ldots, T.
\]

**Lemma 4.1**

(i) For all \( A_T \in \mathcal{A}_T \) the matrix norm induced by \( \|\cdot\|_T \) satisfies
\[
\|A_T\|_T \leq 1.
\] (42)

(ii) The subspace
\[
W := \{ z \in \mathbb{R}^{Tn} \mid e^\top z_i = 0, \forall i = 1, \ldots, T \}
\] (43)
is invariant under all \( A_T \in \mathcal{A}_T \).

(iii) For all \( z \in W, A_T \in \mathcal{A}_T \) it holds that
\[
\|A_T z\|_T = \|z\|_T \quad \Rightarrow \quad A z_1 = z_1.
\]

In particular, we have
\[
\|A_T z\|_W \leq \frac{c + T - 1}{T} < 1,
\] (44)
where \( c < 1 \) is the constant given by Lemma 2.7.
Proof (i) This is a straightforward calculation.
(ii) This is an easy consequence of $e^TA = e^T, A \in \mathcal{A}$.
(iii) Consider $A \in \mathcal{A}$ and the corresponding matrix $A_T \in \mathcal{A}_T$. Assume that $\|A_Tz\|_T = \|z\|_T$ and consider an index $i$ such that $\|z\|_T > \|z_i\|_1$. As $\|A\|_1 \leq 1$, it follows that

$$\|(A_Tz)_{i+1}\|_1 = \left\|\frac{1}{i+1}Az_1 + \frac{i}{i+1}z_i\right\|_1 < \|z\|_T.$$ 

Thus if $\|A_Tz\|_T = \|z\|_T$ then necessarily $(1/(i+1))Az_1 + (i/(i+1))z_i = \|z_i\|_1$ for an index $i$ such that $\|z_i\|_1$ is maximal. Also we may assume that $i < T$. As $\|A\|_1 \leq 1$ it follows that $\|Az_i\|_1 = \|z_i\|_1$ and so $\|z\|_1 = \|Az_1\|_1 = \|z_1\|_1$ as $\|z_i\|_1$ was maximal. Now it is known for the matrices $A \in \mathcal{A}$, that $\|z\|_1 = \|Az_1\|_1, e^TAz_1 = 0$ implies that $Az_1 = z_1$. [17] Lemma 3.8. Finally,

$$\|A_{T,1}z\|_T = \max_{i=1 \ldots T} \left\|\frac{1}{i}Az_1 + \frac{i-1}{i}z_{i-1}\right\|_1 \leq \max_{i=1 \ldots T} \left\{\frac{c}{i} \|z_1\|_1 + \frac{i-1}{i} \|z_{i-1}\|_1\right\} \leq \max_{i=1 \ldots T} \left\{\frac{c}{i} + \frac{i-1}{i}\right\} \|z_T\|_T.$$ 

This shows the assertion.

The previous result shows that the iteration of random choices of the $A_{T,i}$ is contractive when studied with respect to a suitable norm. This lies the foundation for proving the existence of a unique invariant and attractive measure for the Markov chain. Before proving this we need an assumption on the probability functions $\lambda_i$ that guarantees strong contractivity on average.

Theorem 4.2 (Invariant Measure) Assume that the probability functions $\lambda_i$ satisfy (A1)-(A3) and are Lipschitz continuous. Then for all $T \geq 1$, there exists a unique invariant and attractive measure $\pi^T$ on $\Sigma^T$. Furthermore, for all $z_0 \in \Sigma^T$, we have that almost surely

$$\lim_{k \to \infty} \frac{1}{k} \sum_{\ell=0}^{k} z(\ell; z_0) = \int_{\Sigma^T} z \ d\pi^T(z) = E(\pi^T).$$

(45)

Remark 4.3 Stronger ergodicity results hold as detailed in [2] [17]. We skip these for the sake of brevity.

Proof It is easy to show that the sufficient conditions provided in [2] are satisfied. In particular, these conditions can be met by requiring that

$$\sup_{z, w \in \Sigma} \sum_{A_T \in \mathcal{A}_T} p_A(z) \frac{\|A_T(z - w)\|_T}{\|z - w\|_T} < 1.$$ 

(46)

Note that $z - w \in W$, so Lemma 4.1(iii) immediately implies that the sum does not exceed 1. Assumption (A3) now ensures that for each $z \in \Sigma$, the probability $p_1(z) \geq \lambda_{\text{min}} > 0$. Thus the probability of the matrix $A_1$ is bounded away from zero. Now Lemma 4.1(iii) states that $\|A_{T-1}(z - w)\| \leq (c + T - 1)/T \|z - w\| < \|z - w\|$. As $p_1(z) > 0$ for all $z$, we see that the supremum in (46) is bounded away from 1.

The final condition that needs to be satisfied is that there exists a constant $r < 1$ and a constant $\gamma > 0$ such that for all $z, w \in \Sigma$ we have

$$\sum_{A_T \in \mathcal{A}_T \|A_T(z - w)\|_T \leq r} p_A(z) p_A(w) = \gamma > 0.$$ 

(47)

In our situation, this is clear as $p_1(z) > \lambda_{\text{min}} > 0$ for all $z \in \Sigma$. This implies that we may choose $\gamma = \lambda_{\text{min}}^2$ in (47). By Theorem 2.1 in [2] the existence of an attractive invariant measure follows. Uniqueness is then a consequence of attractivity. The ergodic property now follows from [17].

Remark 4.4 The previous results show that the AIMD system is indeed converging in a strong sense; in particular, long term averages converge almost surely. Simulations suggest, that this limit gets closer to the KKT point as $T$ increases. Also for large $T$, with high probability along a sample path, the average of the windows of size $T$ is close to the KKT point.
4.2 Long-Term Averaging

We now turn to the situation in which the probabilities for choosing the matrices depend on the long-term average of the realization. Note that (34) together with (38) do not define a Markov chain on $\Sigma$, as the probabilities do not depend on the current state $x(k)$ but rather on the complete history of a sample path. In order to obtain a formulation as a Markov chain we include the average in the state space. To this end we introduce the new random variable

$$z(k) := [x(k)\top \bar{x}(k)\top]\top.$$  

It follows from the definition of $\bar{x}(k)$ in (37) that $\bar{x}(0) = x_0$ and

$$\bar{x}(k+1) = 1_{k+2} x(k+1) + \frac{k+1}{k+2} \bar{x}(k).$$  

(48)

Hence $z(k)$ evolves according to

$$z(k+1) = \tilde{A}(k)z(k),$$  

(49)

where

$$\tilde{A}(k) := \begin{bmatrix} A(k) & 0 \\ \frac{1}{k+2} A(k) & \frac{k+1}{k+2} I \end{bmatrix}.$$  

(50)

Given $A \in \mathcal{A}$, we introduce the matrices

$$A_{LTA}(k) := \begin{bmatrix} A & 0 \\ \frac{1}{k+2} A & \frac{k+1}{k+2} I \end{bmatrix}, \quad k = 0, 1, \ldots.$$  

(51)

Then, for all $y \in \Sigma$, we have the conditional probabilities

$$\mathbb{P}(\tilde{A}(k) = A_{LTA}(k) \mid \bar{x}(k) = y) = p_A(y).$$  

(52)

This defines a nonhomogeneous Markov chain with place-dependent probabilities. Note that the nonhomogeneity comes from the time-varying nature of the matrices $A_{LTA}(k)$, whereas the functions $p_A(\cdot)$ describing the place-dependent probabilities do not depend on time.

To obtain contractive properties of the Markov chain (49) it will be of interest to study the matrices $A_{LTA}(k)$ using a particular norm. We define a norm on $\mathbb{R}^{2n \times 2n}$ by setting for $x, y \in \mathbb{R}^n$

$$\| [x \ y] \| := \max \{\|x\|_1, \|y\|_1 \}.$$  

(53)

The matrix norm induced by this vector on $\mathbb{R}^{2n \times 2n}$ is also denoted by $\| \cdot \|$.

In the following we use the notation $A_{LTA} := \{A_{LTA}(k) \mid A \in \mathcal{A}, k \in \mathbb{N} \}$, which represents the set of all possible matrices appearing in (49).

Lemma 4.5  

(i) For all $A_{LTA} \in A_{LTA}$

$$\|A_{LTA}\| \leq 1.$$  

(54)

(ii) The subspace

$$W := \{(x, y) \in \mathbb{R}^{2n} \mid e^\top x = e^\top y = 0\}$$  

(55)

is invariant under all $A_{LTA} \in A_{LTA}$.

Proof The proof follows the lines of the proof of Lemma 4.1 and is omitted.

We stress that the key point of Lemma 4.1 was item (iii), which we used to obtain a uniform contractivity on the state space $\Sigma^T$ of the Markov chain. A similar result can be obtained in the present situation, but uniformity is lost due to the time-dependent nature of the Markov chain. Unfortunately, the constant of contraction converges to 1. Considerable effort has been expensed on trying to transfer the proofs of [2, 17] to the present situation, but to no avail. We thus pursue an entirely different angle of attack in the proof of our main result.
Theorem 4.6 (Convergence) Let the functions $\lambda_i$ defined in (33) satisfy (A1)–(A3) and let $x^*$ denote the KKT point guaranteed by Lemma B.1. Consider the nonhomogeneous Markov chain (49). For any initial condition $z(0) = (x_0, \bar{x}_0) \in \Sigma^2$ we have that the second component of $z(k)$ satisfies
\[ \lim_{k \to \infty} \bar{x}(k) = x^* \quad \text{almost surely} \quad \mathbb{P}_{x_0}. \]

Remark 4.7 Our result says that by local modification of the individual probabilities the agents can ensure almost sure convergence to the optimum. Inter-agent communication is not necessary; rather the only information needed is a 1-bit intermittent message to all agents that a capacity event has occurred. This minimal information suffices for convergence. The main results of this section are the following:

1. an ergodicity result for the algorithm with finite-averaging;
2. a result guaranteeing almost sure convergence to the network optimum for the long-term averaging case;
3. the description of an easily implementable algorithms that ensures the convergence of the algorithm to the optimal point, using limited uniform communication to the agents. The algorithm is particularly suited to dumb devices that do not have extensive computational capabilities.

Mathematically speaking, it is interesting to see an almost sure convergence result, that does not make use of the existence of an invariant measure of the stochastic process. We do expect however, that when considering the invariant measures $\pi^T$ that are obtained for the case of finite time-windows, then as $T \to \infty$ the measures $\pi^T$ converge to the Dirac measure in $x^*$.

5 Related Works

Our work lies in the intersection of two subjects: resource allocation and limiting characteristics of the stochastic version of the AIMD algorithm [23].

The AIMD literature is huge and it is not straightforward to discuss the available results in any sort of compact manner here. We refer interested readers to some recent works on this topic in the context of TCP and internet congestion control [31, 34, 28, 48, 36, 50, 27, 20]. Much of this work is based on fluid approximations of AIMD dynamics; the notable exceptions are [44, 40, 43]. The latter of these papers make use of tools from iterated function systems to deduce the existence of such a unique probability distribution for standard linear AIMD networks (of which TCP is an example) under an assumption on the underlying probability model (albeit under very restrictive assumptions). To the best of our knowledge, this paper, along with the companion paper [44], established for the first time, the stochastic convergence of AIMD networks. However, the window of infinite length considered in this paper goes well beyond the set-up in these papers. In particular, the result presented in this paper may be considered as the limiting case of the results presented in these papers.

The literature on resource allocation is also immense and a full review is impossible here. Here, we briefly note that the subject of resource allocation or social welfare optimization has been studied in three prominent settings: centralized, distributed concerted, and distributed competitive.

In the first setting, there is a single decision-maker, who knows the utility function $f_i$ of every agent, solves the network optimization problem, and assign the optimal allocation to each agent.

In the second setting, every resource user is a decision-maker that determines its own allocation according to a fixed policy (e.g., AIMD algorithm in the case of TCP), that is prescribed by a system operator and remains unchanged over time. When all agents follow fixed policies prescribed by the system operator, a number of distributed optimization algorithms have been proposed to iteratively converge to an optimal allocation of resources for numerous settings [16, 57, 24, 59]. Some of these algorithms are based on achieving consensus [57], others are based on distributed averaging [52, 34], and on stochastic approximation [3]. All these algorithms rely on communication between agents to achieve optimality. For example, when agents are assigned to nodes in a graph and restricted to communicate only with
neighbors in that graph, the distributed dual averaging algorithm has been shown to guarantee the convergence of each agent’s allocation to the optimal allocation over iterations of the algorithm [16]. Our work also considers a distributed setting with fixed-policy agents, but contains an important difference: the agents do not communicate among themselves, but are limited to an intermittent feedback signal from the network. Specifically, they only observe at each iteration whether the allocation is feasible (i.e., the capacity constraint is satisfied). Another difference of our work is that our results do not depend on the existing convergence results from stochastic approximation, and hence hold under different conditions. In particular, we cannot apply the standard convergence argument for stochastic approximation because there are two time-scales (cf. [6] Chapters 6.2 and 10.4).

In a third setting, every resource user is a decision-maker that acts strategically so as to optimize its utility function with regards to the actions of all agents. When all agents act strategically, solution concepts such as Nash equilibria are more meaningful than optimality concepts. In such a setting, a market mechanism based on bids has been proposed [25] and shown to be efficient in equilibrium under some assumptions [51]. In this situation the equilibrium allocation is also the solution to an optimization problem. These works do not however provide a method for the agents to arrive at an equilibrium allocation. In contrast, our work may not consider strategic agents, but does present a set of policies that guarantee the convergence to an optimal allocation.

The link between congestion control (which encompasses the AIMD algorithm) and optimization has been noted by several authors [25, 29, 30, 45, 9, 47, 26, 14]. That various embodiments of TCP solve a network utility maximization problem is a cornerstone of much of the TCP literature [45]. However, we are dealing with the converse problem: given an NUM problem, is there an AIMD algorithm that solves it? Perhaps, the most closely related works in this direction are given in the following references: [29, 9, 47, 26, 14]. Roughly speaking, these references follow two lines of direction. In the first direction, fluid-like approximations of congestion control are modified to address the NUM problem. This yields a sub-gradient like algorithm for solving the NUM problem. In the second direction, synchronized AIMD like algorithms are proposed to solve certain NUM problems using nonlinear back-off rules and nonlinear increase rules [13, 47, 26, 14]. The work presented here goes far beyond these works. First, we consider the matrix model of TCP proposed in [44] as opposed to a fluid model. Fluid approximations are valid only for very large numbers of agents, and the dynamic interaction between agents is often overlooked. The matrix model is an exact representation of AIMD dynamics under certain assumptions and can readily be implemented in existing software stacks. Furthermore, these models are often analyzed using linearized approximations in contrast to our approach in which global stability (ergodicity) is proved. A further difference is that each agent responds to a capacity event according to its own probability function, known only to that agent. In this sense our proposed algorithms go beyond traditional AIMD and emulate RED-like congestion control [45]. Second, we assume very limited actuation; an agent only decides to respond to a capacity event or not in an asynchronous manner. There is no need for a common clock and the setting is completely stochastic. In this context our results prove convergence and stability of the stochastic AIMD system and establish its suitability for solving large scale NUM problems.

6 Example

We now illustrate the application of our results. To this end consider a total of $n = 150$ agents participating in the optimization. Each agent $i$ has a cost function $f_i$ assigned which maps its share of the resource capacity $C$ to an associated cost. The cost functions are chosen from the set of polynomials taking the following forms

\[
g_1(\bar{x}) = a_1 \bar{x}^2 \\
g_2(\bar{x}) = a_2 \bar{x}^2 + b_2 \bar{x}^3 \\
g_3(\bar{x}) = a_3 \bar{x}^2 + b_3 \bar{x}^3 + c_3 \bar{x}^4 \\
g_4(\bar{x}) = a_4 \bar{x}^2 + b_4 \bar{x}^4 + c_4 \bar{x}^6
\]
The parameters \(a_j, b_j\), and \(c_j\) are the cost-factors of each function and are positive. Note that each function is convex and strictly increasing on the interval \([0, C]\). The objective is then

\[
\min_{\bar{x}_1, \ldots, \bar{x}_n} \sum_{i=1}^{n} f_i(\bar{x}_i)
\]
\[
\text{s.t. } \sum_{i=1}^{n} \bar{x}_i = C.
\]

For the simulations we choose the resource capacity to be equal to one, i.e. \(C = 1\). Further, the cost-function type for each agent is selected randomly according to a uniform distribution. The cost-factors parameters for each agent are also selected randomly using a uniform distribution between 0 and 100.

Defining

\[
\lambda_i(r) = \Gamma f'_i(r) r,
\]

(57)

each agent responds to a capacity event with probability

\[
\lambda_i(\bar{x}_i(k))
\]

(58)

with \(\bar{x}_i(k)\) as in (37) in case of long-term averaging and

\[
\lambda_i(\bar{x}_i,T(k))
\]

(59)

with \(\bar{x}_i,T(k)\) as in (35) in case of finite averaging. Here \(\Gamma\) is a network wide constant chosen to ensure that \(0 < \lambda_i(r) < 1\) for \(0 \leq r \leq 1\). In our simulations we set \(\Gamma = \frac{1}{1300}\). The remaining AIMD parameters are identical for all agents with \(\alpha = 0.01\) and \(\beta = 0.85\). From our main result we know that for large \(k\) we have that \(\bar{x}_i(k) \approx x_i^*\). Thus we can write \(\lambda_i(\bar{x}_i(k)) \approx \lambda_i^*\). It follows that

\[
\lambda_i(\bar{x}_i(k)) \approx \Gamma f'_i(\bar{x}_i(k)) \Theta \lambda_i(\bar{x}_i(k))
\]

(60)

and that \(f'_i(\bar{x}_i(k)) \approx f'_j(\bar{x}_j(k))\) for all \(i, j\) and large \(k\), and where \(\Theta\) is a network constant. These are precisely the KKT conditions. We first simulate the long-term averaging case, where the average at time instant \(k\) is taken over all previous time-steps. Figure 1 shows the typical evolution of the derivative of the cost of seven randomly selected agents. It illustrates that the derivatives approach consensus as \(k\) increases; this results in the the above stated optimization problem being solved asymptotically.

Figure 2(a) shows the long-term average state \(\bar{x}_i(k)\) of seven randomly chosen agents in comparison to their respective optimal state \(x_i^*\) depicted by a dashed line. Figure 2(b) shows the absolute error between the long-term average and the optimal state for the same seven agents. With increasing time the long-term average approaches the optimal state for those seven randomly selected agents. In Figure 3 the maximal error between the long-term average and the optimal state is plotted, which approaches zero with increasing time.

We repeat our experiment for the finite averaging case, with a fixed window size \(T = 500\). Figure 4 shows the typical evolution of the derivative of the cost function for seven randomly selected agents. It illustrates that these derivatives are oscillating around the optimal value.

Figure 5 shows the maximal error between the long-term average and the optimal state. Recall, that in these simulations the long term average is not used for determining the drop probabilities. Its limit exists almost surely and is given by the expectation of the underlying invariant measure, see Theorem 4.2. While the cost computed with the finite average is oscillating, the long term average of the state is still converging towards the optimal value.

Note that we have made several assumptions. First, we have assumed that eventually \(\bar{x}_i(k) \approx x_i^*\). This follows from our main result. We have also assumed that \(p_i(k) \approx p_i^*\). This follows from continuity of the \(f_i(\cdot)\).
Figure 1: Evolution of the cost derivatives for seven randomly selected agents.

Figure 2: Evolution of the states in comparison to the optimal point for seven randomly selected agents.

Figure 3: Evolution of the maximal absolute error between the states and the optimal states, i.e. $||\bar{x}(k) - x^*||_\infty$.  

(a) $\bar{x}_i(k)$ (solid) and $x^*_i$ (dashed) 

(b) $|\bar{x}_i(k) - x^*_i|$
Figure 4: Evolution of the derivatives for seven randomly selected agents. The simulations are done for the finite averaging case with a fixed window size $T = 500$.

Figure 5: Evolution of the maximal absolute error between the states and the optimal, i.e. $\|\bar{x}(k) - x^*\|_{\infty}$. The simulations are done for the finite averaging case with a fixed window size $T = 500$. 
7 Conclusions

In this paper we have derived a convergence result for the non-homogeneous Markov chain that arises in the study of networks employing the additive-increase multiplicative decrease (AIMD) algorithm. We then used this result to solve the network utility maximization problem in a very simple manner. Future work will consider the behavior of finite window averaging systems and elaborate on the preliminary results obtained in this paper.

We have also applied our approach to the distributed optimization of agents that have two possible states—ON and OFF—and finite memory. Initial, but extensive, simulation studies suggest that our results hold in this setting as well. Finally, it is worthwhile to note that it is possible to extend our results in the following directions: allowing updates to the increase and decrease parameters ($\alpha_i$ and $\beta_i$) over time to achieve faster convergence to optimality, allowing agents leaving and joining the allocation system over time, and allowing the joint allocation of multiple resources; e.g., bandwidth over distinct links of a communication network, or a combination of bandwidth and computation resources in a cloud server.

Appendix

A Preamble to the Proofs

We now briefly explain the structure of the proof of the main result, as otherwise the reader may sometimes wonder why we need certain intermediate results.

The key intuition is that in the long run, the long term average $\bar{x}$ changes slowly. In other words, for large $T$ and relatively short intervals of length $m$ of the form $[T, T + m]$, $\bar{x}$ is almost a constant, where $m$ is to be understood to be small when compared to $T$. The reason for this is the simple relation

$$\bar{x}(T + m) = \frac{T + 1}{T + 1 + m} \bar{x}(T) + \frac{m}{T + 1 + m} \left( \frac{1}{m} \sum_{\ell=1}^{m} x(T + \ell) \right),$$

(61)

which holds along any sample path.

If $\bar{x}$ is almost a constant on a certain interval, then the probabilities for choosing the matrices $A \in \mathcal{A}$ are almost constant, and we can approximate the dynamics using the results on AIMD with constant probabilities; and consequently Lemma 2.2 becomes relevant. This result says that, provided that $m$ is large enough, the average over the next $m$ steps is close to the expectation of the AIMD Markov chain with constant probabilities. And this holds for all starting conditions $x(T)$ and with high probability.

While this basic intuition turns out to be true, we need to resolve the fact that the ergodic limit of the “fixed-probability system” depends on $T$. Specifically, $m$ and $T$ depend on each other and the precise resolution of our proof depends on understanding this relationship.

To resolve this, we use the following interpretation of (61). For $y \in \Sigma$, we denote by $P(y)$ the expectation of the invariant measure of the IID AIMD process with fixed probabilities $\lambda_1(y_1), \ldots, \lambda_n(y_n)$, that is,

$$P(y) = \xi_{\lambda(y)},$$

(62)

where

$$\lambda(y) = \left[ \begin{array}{c} \lambda_1(y_1) \\ \vdots \\ \lambda_n(y_n) \end{array} \right].$$

We then rewrite (61) as

$$\bar{x}(T + m) = \frac{T + 1}{T + 1 + m} \bar{x}(T) + \frac{m}{T + 1 + m} \left( P(\bar{x}(T)) + \Delta(T) \right),$$

(63)

where we interpret $\Delta(T)$ as a suitable perturbation term, that aggregates the effect that the probabilities are not precisely constant on $[T + 1, T + m]$, and the further effect that we are not at the expectation...
AIMD and Optimization

but only close to it.

To understand the dynamics in (63) we study the system

$$\bar{x}(T + m) = \frac{T + 1}{T + 1 + m} \bar{x}(T) + \frac{m}{T + 1 + m} P(\bar{x}(T)),$$

(64)

and interpret system (63) as a perturbed version thereof. This is the sole purpose of Appendix B, in which we obtain (i) characterizations of the unique fixed point of (64), (ii) characterizations of attractivity properties of neighborhoods of this fixed point in dependence of the size of $m/(T + m)$, and (iii) the necessary robustness results to extend these attractivity statements to the perturbed system (63). In Appendix C we then bring the stochastic nature of our nonhomogeneous Markov chain into play and use the results of Appendix B to prove almost sure convergence using what is essentially a Lyapunov type argument.

B Deterministic Iteration

In this section we present a collection of stability and robustness results for a deterministic system closely related to the AIMD Markov chain. These results will turn out to be instrumental in the proof of the main result Theorem 4.6.

The first results study a deterministic system defined by successive convex combinations of a point in $\Sigma$ with the expectation of this point as defined through (16).

Recall, that we assume that $\alpha \in \text{ri } \Sigma$ and $\beta \in (0,1)^n$ satisfy the assumption that the quotient $\alpha_i/(1 - \beta_i)$ is a constant independent of $i$. As a consequence the limiting value defined in (16) simplify. Given the probabilities $\lambda_1, \ldots, \lambda_n$ the expression reduces to

$$\xi = 1/\sum_{\ell=1}^n \lambda_\ell^{-1} \left[ \begin{array}{c} \lambda_1^{-1} \\ \vdots \\ \lambda_n^{-1} \end{array} \right].$$

(65)

We thus arrive at the map $P : \Sigma \rightarrow \Sigma$ given by

$$P(x) = \Theta(x) \left[ \begin{array}{c} \lambda_1(x_1)^{-1} \\ \vdots \\ \lambda_n(x_n)^{-1} \end{array} \right] \quad \text{with} \quad \Theta(x) = 1/\sum_{\ell=1}^n \lambda_\ell(x_\ell)^{-1}.$$

(66)

Note that $P(\Sigma) \subset \text{ri } \Sigma$ is compact by (A3). We may therefore choose a constant $\delta^- > 0$ such that

$$P(\Sigma) + \overline{B}_1(0, \delta^-) \subset \text{conv } P(\Sigma) + \overline{B}_1(0, 2\delta^-) \subset \text{ri } \Sigma.$$

(67)

Note that in this instance, and in the following, scalings and sums of sets are in the standard sense of Minkowski sums. Also the factor 2 is an arbitrarily chosen factor that will become useful in later robustness estimates. All that is required is that this factor exceeds 1. Furthermore, we require the constant

$$\delta^+ := \max \{ \text{dist}_{\Sigma}(y, P(\Sigma)) : y \in \Sigma \}.$$

(68)

We will be interested in systems that perform successive convex combinations of the state $x$ and $P(x)$. For $\{\varepsilon_k\}_{k \in \mathbb{N}} \subset (0,1)$ consider the system

$$x(k + 1) = (1 - \varepsilon_k)x(k) + \varepsilon_k P(x(k)).$$

(69)

We note the following simple properties of the iteration in (69).
Lemma B.1 Suppose that Assumptions (A1)-(A3) hold and \( n \geq 2 \). Let \( \alpha \in \text{ri} \Sigma_n \) and \( \beta \in (0,1)^n \) be such that \( \alpha_i/(1-\beta_i) \) is independent of \( i \). Then \( P \) has the following properties.

(i) \( P \) has a fixed point, that is, there is a vector \( x^* \in \Sigma \) with \( P(x^*) = x^* \).

(ii) The fixed point \( x^* \) is unique and is characterized by the property

\[
x_i^* \lambda_i(x_i^*) = x_j^* \lambda_j(x_j^*) := \gamma_F \quad \text{for all} \quad i, j \in \{1, \ldots, n\}.
\]

(iii) For every \( \varepsilon \in (0,1] \) the fixed point \( x^* \) of \( P \) is the unique fixed point of

\[
x \mapsto (1 - \varepsilon)x + \varepsilon P(x).
\]

(iv) For every \( x_0 \in \Sigma \) and every sequence \( \{\varepsilon_k\}_{k \in \mathbb{N}} \subset (0,1) \) the solution of (69) satisfies \( x(k) \gg 0 \) for all \( k \geq 1 \).

Proof (i) As \( P : \Sigma \to \Sigma \) is continuous and \( \Sigma \) is compact and convex, the existence of a fixed point for \( P \) follows from Brouwer's fixed point theorem.

(ii) Letting \( \gamma(x^*) := \sum_{i=1}^n 1/\lambda_i(x_i^*) \), it follows from the definition of \( P \) that a fixed point \( x^* \) is characterized by

\[
\frac{\gamma(x^*)}{\lambda_i(x_i^*)} = x_i^*
\]

for \( i = 1, \ldots, n \), that is,

\[
\lambda_i(x_i^*) x_i^* = \gamma(x^*)
\]

Suppose that there are two fixed points \( x^* \neq y^* \) for \( P \). Since \( x^*, y^* \in \Sigma \), there are indices \( i \) and \( j \) such that \( x_i^* > y_i^* \) and \( x_j^* < y_j^* \). Also,

\[
x_i^* \lambda_i(x_i^*) = x_j^* \lambda_j(x_j^*) \quad \text{and} \quad y_i^* \lambda_i(y_i^*) = y_j^* \lambda_j(y_j^*).
\]

But from Assumption (A2) we have \( x_i^* \lambda_i(x_i^*) > y_i^* \lambda_i(y_i^*) = y_j^* \lambda_j(y_j^*) > x_j^* \lambda_j(x_j^*) \). This contradiction completes the proof.

(iii) This is an immediate consequence of (i).

(iv) This follows as \( P(x) \gg 0 \) for all \( x \in \Sigma \) by definition and using Assumption (A3). \( \blacksquare \)

In order to simplify notation, we introduce for \( \varepsilon \in [0,1] \) the map \( R_\varepsilon : \Sigma \to \Sigma \) by

\[
R_\varepsilon(x) := (1 - \varepsilon)x + \varepsilon P(x).
\]

Lemma B.1 tells us that for \( \varepsilon \in (0,1] \) the fixed point \( x^* \) of \( P \) is also the unique fixed point of \( R_\varepsilon \).

In our analysis of the dynamics we require two types of contractive properties of the map \( R_\varepsilon \) in combination with robustness results. We will also consider set-valued maps of the form

\[
\Psi_\delta^\varepsilon(x) := R_\varepsilon(x) + \varepsilon \overline{B}_1(0, \delta) = (1 - \varepsilon)x + \varepsilon (P(x) + \overline{B}_1(0, \delta)),
\]

where we assume \( 0 < \delta < \delta^- \). Note that by definition of \( \delta^- \) this ensures that \( \Psi_\delta^\varepsilon(x) \subset \text{ri} \Sigma \). In the following lemma, we analyze properties of the map \( \Psi_\delta^\varepsilon \) by studying individual elements in its image.

The next result describes two important features of the iteration

\[
x(k + 1) \in \Psi_\delta^\varepsilon(x(k)).
\]

On one hand by (i) the iteration converges with rate \((1 - \varepsilon)\) to the convex set

\[
P_{co}(\delta) := \text{conv} (P(\Sigma) + \overline{B}_1(0, \delta))
\]

On the other hand using (ii) if the iteration is perturbed so that all we know that there is a convex combination with some \( y \in \Sigma \) then we may bound the increase of the distance to the convex set. Finally, by (iii) the error induced by the perturbation \( y \) can be linearly bounded in \( \varepsilon \), provided that we are sufficiently far way from \( P_{co}(\delta) \). For the following statement recall the definition of \( \delta^- \) in (67).
Lemma B.2 Let $x \in \Sigma$. Then for all $0 < \varepsilon \leq 1$:

(i) For all $0 < \delta < \delta^-$ and $\Delta \in \mathbb{R}^n, e^\top \Delta = 0, \|\Delta\|_1 \leq \delta$ we have
\[
\text{dist}_1(R_c(x) + \varepsilon \Delta, P_{co}(\delta)) \leq (1 - \varepsilon)\text{dist}_1(x, P_{co}(\delta)) .
\] (74)

(ii) In view of (68), for all $0 < \delta < \delta^-$ and all $y \in \Sigma$, we have
\[
\text{dist}_1((1 - \varepsilon)x + \varepsilon y, P_{co}(\delta)) \leq (1 - \varepsilon)\text{dist}_1(x, P_{co}(\delta)) + \varepsilon \delta^+ .
\] (75)

(iii) For every $0 < \delta < \delta^-$ there exists a $C_\delta > 0$ such that for all $0 < \varepsilon < 1$ and all $0 < \delta < \delta^-$ we have the following implication: If $x \in \Sigma$ satisfies $\text{dist}_1(x, P_{co}(\delta)) > \delta$ and $y \in \Sigma$, then
\[
\text{dist}_1((1 - \varepsilon)x + \varepsilon y, P_{co}(\delta)) \leq (1 + C_\delta \varepsilon)\text{dist}_1(x, P_{co}(\delta)) .
\] (76)

Proof (i) Let $z \in P_{co}(\delta)$ be such that
\[
\|x - z\|_1 = \text{dist}_1(x, P_{co}(\delta)) .
\]
Then by convexity $(1 - \varepsilon)z + \varepsilon(P(x) + \Delta) \in P_{co}(\delta)$ and so
\[
\text{dist}_1(R_c(x) + \varepsilon \Delta, P_{co}(\delta)) \leq \|(R_c(x) + \varepsilon \Delta) - ((1 - \varepsilon)z + \varepsilon(P(x) + \Delta))\|_1 = (1 - \varepsilon)\|x - z\|_1 .
\]

(ii) To prove (75) note that for any convex set $C$, we have $C = (1 - \varepsilon)C + \varepsilon C$. Hence,
\[
\text{dist}_1((1 - \varepsilon)x + \varepsilon y, P_{co}(\delta)) \leq (1 - \varepsilon)\text{dist}_1(x, P_{co}(\delta)) + \varepsilon \text{dist}_1(y, P_{co}(\delta)) ,
\]
which shows the claim by definition of $\delta^+$.

(iii) To prove (76) note that with the assumption $\text{dist}_1(x, P_{co}(\delta)) > \delta$ we arrive at
\[
\delta^+ \leq \delta^+ \frac{\text{dist}_1(x, P_{co}(\delta))}{\delta} ,
\]
and so (76) follows from (75) with an appropriate choice of $C_\delta > 0$. This completes the proof. $\square$

It is the aim of the following sequence of results to establish similar properties close to the fixed point $x^*$. To this end we have found it necessary to work with a different metric. We need the following lemma, for which we will make use of the following elementary observations. First, note the implication
\[
(x \in \text{ri} \Sigma \quad \text{and} \quad x \neq x^*) \quad \Rightarrow \quad \min_j \{x_j/x^*_j\} < 1 < \max_i \{x_i/x^*_i\} .
\] (77)

Using this relation it is straightforward to see that for any sequence $\{x_k\} \subset \text{ri} \Sigma$ we have the equivalence
\[
\varepsilon^{d_R}(x_k, x^*) \to 1 \quad \Leftrightarrow \quad \min_j \{x_{kj}/x^*_j\} \to 1 \quad \Leftrightarrow \quad \max_i \{x_{ki}/x^*_i\} \to 1 .
\] (78)

Lemma B.3 Let $x^* \in \Sigma$ be the unique fixed point of $P$, as described in Lemma B.1. For every $\eta > 0$, there are constants $0 < r < 1 < R$ and a constant $\varepsilon_0 \in (0, 1)$ such that for all $0 < \varepsilon < \varepsilon_0$ we have that if $d_R(x, x^*) > \eta$ and $i, j$ are such that
\[
\varepsilon^{d_R}(R_c(x), x^*) = \frac{R_c(x)_i/x^*_i}{R_c(x)_j/x^*_j} ,
\] (79)
then $x_i > R x^*_i$ and $x_j < r x^*_j$. 


Proof Let $\eta > 0$ be fixed. By (78) there exists a constant $r_1 \in (0, 1)$ such that for all $x \in \text{ri} \Sigma$ with $d_H(x, \mathbf{x}^*) \geq \eta$ we have

$$\min_{j=1,\ldots,n} \frac{x_j}{x_j^*} \leq r_1 < 1. \quad (80)$$

Using (A3) and $\lambda_i(x_i) \in [\lambda_{\text{min}}, 1]$, we have for all $x \in \Sigma$, $i = 1, \ldots, n$ that

$$x_i^* > 0, x_i^* := \min_{i=1}^{n} x_i^* > 0.$$

Define $x_i^*: \min_{i=1}^{n} x_i^* > 0$. Choose $r, r_2$ such that $0 < r_1 < r < 1$ and $\epsilon_1 > 0$ such that we have for all $\epsilon \in (0, \epsilon_1)$ that

$$\frac{1}{x_j^*} < \frac{\epsilon}{x_j^*} < \frac{\epsilon}{x_j^*} < r_2 < (1 - \epsilon) \frac{r_1}{x_j^*} \epsilon c_2 < r_2. \quad (82)$$

With this choice it follows that if $x_j^*/x_j^* \leq r_1$ and $0 < \epsilon < \epsilon_1$ then

$$\frac{R_e(x_j)}{x_j^*} = (1 - \epsilon) x_j + \epsilon P_j(x) \leq (1 - \epsilon) r_1 + \epsilon \frac{c_2}{x_j^*} < r_2. \quad (83)$$

On the other hand, if $x_j^*/x_j^* \geq r$ and $0 < \epsilon < \epsilon_1$ then

$$\frac{R_e(x_j)}{x_j^*} = (1 - \epsilon) x_j + \epsilon P_j(x) \geq (1 - \epsilon) r + \epsilon \frac{c_1}{x_j^*} > r_2. \quad (84)$$

Combining (83) and (84) we see that if $d_H(x, \mathbf{x}^*) \geq \eta$ and $r, \epsilon_1$ are chosen as above then (79) implies that $x_j < r x_j^*$, as desired.

The claim for the upper bound $x_i \geq R e(x, \mathbf{x}^*)$ follows with a similar argument. To this end note that by (78), there exists a constant $R_1$ such that for all $x \in \text{ri} \Sigma$ with $d_H(x, \mathbf{x}^*) \geq \eta$ we have

$$\max_{i=1,\ldots,n} x_i^* \geq R_1 > 1. \quad (85)$$

The claim then follows by another application of (81).

The following result is a cornerstone in our proof of the main result.

**Theorem B.4** Let $\mathbf{x}^* \in \Sigma$ be the unique fixed point of $P$, as described in Lemma B.4. For every $\eta > 0$, there is $0 < \epsilon_0$ such that for all $0 < \epsilon < \epsilon_0$ we have

$$d_H(x, \mathbf{x}^*) > \eta \quad \Rightarrow \quad d_H(R_e(x), \mathbf{x}^*) < d_H(x, \mathbf{x}^*). \quad (86)$$

**Proof** If $x \in \Sigma$ and some entries of $x$ are zero, then $d_H(x, \mathbf{x}^*) = \infty$, and also $R_e(x) \gg 0$ by construction. Thus the claim follows trivially. In the remainder of the proof we will thus assume that $x \gg 0$.

Fix $\eta > 0$. By Lemma B.3 we may choose a constant $\epsilon_1 \in (0, 1)$ such that if $d_H(x, \mathbf{x}^*) > \eta$ and if $i, j$ are such that

$$\epsilon^{d_n}(R_e(x), \mathbf{x}^*) = \frac{R_e(x_i)/x_i^*}{R_e(x_j)/x_j^*}, \quad (87)$$

then $x_i > x_i^*$ and $x_j < x_j^*$.

For the case $x_i > x_i^*$, we obtain using the constant $\gamma_F$ defined in (70) and the fact that $x_i \lambda_i(x_i) > \gamma_F$ by assumption (A2) that

$$R_e(x_i) = (1 - \epsilon)x_i + \epsilon \sum_{\nu=1}^{n} x_\nu \lambda_\nu \epsilon, \quad (88)$$

By a similar argument, if $x_j < x_j^*$ we obtain

$$R_e(x_j) = (1 - \epsilon)x_j + \epsilon \sum_{\nu=1}^{n} \lambda_\nu \epsilon, \quad (89)$$
Combining (88) and (89), we obtain for the indices $i, j$ such that (87) holds that

$$e^{d_H(R_e(x), x^*)} = \frac{R_e(x)_i / x^*_i}{R_e(x)_j / x^*_j} < \frac{x_i / x^*_i}{x_j / x^*_j} \leq e^{d_H(x, x^*)}. \quad (90)$$

This completes the proof.

**Corollary B.5** Let $x^* \in \Sigma$ be the unique fixed point of $P$, as described in Lemma B.1. For every $\eta > 0$, there is $1 > \varepsilon_0 > 0$ and a constant $C_\eta > 0$ such that for all $0 < \varepsilon < \varepsilon_0$ we have

$$d_H(x, x^*) \geq \eta \quad \Rightarrow \quad e^{d_H(R_e(x), x^*)} < (1 - C_\eta \varepsilon) e^{d_H(x, x^*)}, \quad (91)$$

or equivalently,

$$d_H(x, x^*) \geq \eta \quad \Rightarrow \quad d_H(R_e(x), x^*) < d_H(x, x^*) + \log(1 - C_\eta \varepsilon) < d_H(x, x^*) - C_\eta \varepsilon. \quad (92)$$

**Proof** Fix $\eta > 0$. Let $\varepsilon_0 > 0$ and $r, R$ be the constants corresponding to $\eta$ given by Lemma B.3. Using Assumptions (A1), (A2) and Lemma B.1, there are constants $L_1 < \gamma_F < L_2$ such that

$$x_j \lambda_j(x_j) \leq L_1 \quad \text{for all } j = 1, \ldots, n, \text{ and all } x_j \in [0, 1] \text{ such that } x_j \leq r,$$

$$x_i \lambda_i(x_i) \geq L_2 \quad \text{for all } i = 1, \ldots, n, \text{ and all } x_i \in [0, 1] \text{ such that } x_i \geq R.$$

With this notation we can refine the inequalities (88) and (89). Namely, if $d_H(x, x^*) \geq \eta$ and if $i, j$ are indices such that

$$e^{d_H(R_e(x), x^*)} = \frac{R_e(x)_i / x^*_i}{R_e(x)_j / x^*_j}, \quad (93)$$

then using Lemma B.3 we have $x_i / x^*_i \geq R$, $x_j / x^*_j \leq r$. We obtain following the steps of (88) and (89)

$$e^{d_H(R_e(x), x^*)} = \frac{R_e(x)_i / x^*_i}{R_e(x)_j / x^*_j} < \frac{(1 - \varepsilon) + \sum_{\nu = 1}^{n} \frac{\varepsilon}{\lambda_\nu(x_\nu)} - \frac{1}{L_2}}{(1 - \varepsilon) + \sum_{\nu = 1}^{n} \frac{\varepsilon}{\lambda_\nu(x_\nu)} - \frac{1}{L_1}} \ e^{d_H(x, x^*)}$$

$$= \left(1 - \varepsilon + \frac{\sum_{\nu = 1}^{n} \lambda_\nu(x_\nu)}{1} (1 - \varepsilon) + \frac{\varepsilon}{L_1}\right) \ e^{d_H(x, x^*)}. \quad (94)$$

The term on the right hand side may be bounded by

$$< (1 - C_\eta \varepsilon) e^{d_H(x, x^*)},$$

where

$$C_\eta = \min_{\varepsilon \in [0,1]} \left\{ \frac{L_1 - \frac{1}{L_2}}{\sum_{\nu = 1}^{n} \lambda_\nu(x_\nu) - 1} (1 - \varepsilon) + \frac{\varepsilon}{L_1}\right\} > 0.$$ 

Note that $C_\eta$ depends on $\eta$ as the choice of $r, R$ is a function of $\eta$ and these constants in turn determine possible values for $L_1, L_2$. The final claim follows from a simple application of the logarithm and by using a standard inequality. \qed

We also need the following two robustness results. The first concerns the perturbed averaged system (67), while the second yields a bound on the worst case behavior of convex combination with arbitrary points in $\Sigma$.

**Lemma B.6** Let $x^* \in \Sigma$ be the unique fixed point of $P$, as described in Lemma B.1. Consider $\delta^- > 0$ as defined in (67). There exists a constant $K > 0$ such that for all $0 < \delta < \delta^-$, $\varepsilon \in (0,1)$, all $x \in P_{co}(\delta)$, and all $\Delta \in \mathbb{R}^n$ with $e^T \Delta = 0$ and $\|\Delta\|_1 \leq \delta$ we have

$$e^{d_H(R_e(x) + \varepsilon \Delta, x^*)} - e^{d_H(R_e(x), x^*)} \leq K \varepsilon \delta. \quad (94)$$
\textbf{Proof} The assumption on $\delta$ yields that \( \text{conv} \ P(\Sigma) + \mathcal{B}_1(0, 2\delta) \subset \text{ri} \ \Sigma \). By definition we have
\[
e^{d_H}(R_\varepsilon(x) + \varepsilon \Delta, x^\ast) - e^{d_H}(R_\varepsilon(x), x^\ast) = \max_i \frac{R_\varepsilon(x)_i + \varepsilon \Delta_i/x^\ast_i}{\min_j (R_\varepsilon(x)_j + \varepsilon \Delta_j/x^\ast_j)} - \max_i \frac{R_\varepsilon(x)_i}{\min_j (R_\varepsilon(x)_j/x^\ast_j)}
\]
assuming the \( i, j \) are chosen so that the maximum, resp. minimum is attained for the perturbed term, we may continue
\[
\leq \frac{(R_\varepsilon(x)_1 + \varepsilon \delta)R_\varepsilon(x)_j/x^\ast_j - R_\varepsilon(x)_1(R_\varepsilon(x)_j - \varepsilon \delta)/x^\ast_j}{(R_\varepsilon(x)_j - \varepsilon \delta)R_\varepsilon(x)_j/x^\ast_j} = \varepsilon \delta \frac{(R_\varepsilon(x)_j + R_\varepsilon(x)_1)/x^\ast_j}{(R_\varepsilon(x)_j - \varepsilon \delta)R_\varepsilon(x)_j/x^\ast_j}.
\]
To complete the proof, we need to show that the factor of \( \varepsilon \delta \) in the expression on the right can be uniformly bounded for all \( x \in P_{\text{co}}(\delta) \). By assumption, \( P_{\text{co}}(\delta) \) is a compact subset of \( \text{ri} \ \Sigma \), so that all entries of \( x \) and \( R_\varepsilon(x) \) are bounded away from 0. Furthermore, the terms \( R_\varepsilon(x)_j - \varepsilon \delta \) are bounded away from 0, because for arbitrary indices \( j' \neq j \) we have \( R_\varepsilon(x) - \varepsilon \delta e_j + \varepsilon \delta e_{j'} \in \text{conv} \ P(\Sigma) + \mathcal{B}_1(0, 2\delta) \subset \text{ri} \ \Sigma \). Thus the factor of \( \varepsilon \delta \) in the final expression may be bounded by a constant, because the denominator is bounded away from 0. This constant only depends on \( \delta^{-} \). This proves the claim. \( \square \)

\textbf{Corollary B.7} Let \( x^\ast \in \Sigma \) be the unique fixed point of \( P \), as described in Lemma \[B.1\]. For a given \( \eta > 0 \), let \( 1 > \varepsilon_0 > 0 \) and a \( C_\eta > 0 \) be the constants of Corollary \[B.5\] such that \[01\] and \[02\] hold. Let
\[
\delta^\ast := \min \left\{ \frac{C_\eta \varepsilon_0}{2 \kappa}, \delta^- \right\}.
\]
Then for every \( 0 < \delta < \delta^\ast \), all \( 0 < \varepsilon < \varepsilon_0 \) and all \( x \in \text{conv} \ P(\Sigma) + \mathcal{B}_1(0, \varepsilon) \) and all \( \Delta \in \mathbb{R}^n \), \( \varepsilon^\top \Delta = 0 \), \( \|\Delta\| \leq \delta \) we have \( R_\varepsilon(x) + \varepsilon \Delta \in P_{\text{co}}(\delta) \) and
\[
d_H(x, x^\ast) \geq \eta \ \Rightarrow \ \varepsilon^{d_H}(R_\varepsilon(x) + \varepsilon \Delta, x^\ast) < (1 - \frac{C_\eta}{2})\varepsilon^{d_H}(x, x^\ast), \tag{96}
\]
or equivalently,
\[
d_H(x, x^\ast) \geq \eta \ \Rightarrow \ d_H(R_\varepsilon(x) + \varepsilon \Delta, x^\ast) < d_H(x, x^\ast) + \log \left( 1 - \frac{C_\eta}{2} \varepsilon \right) < d_H(x, x^\ast) - \frac{C_\eta}{2} \varepsilon. \tag{97}
\]
\textbf{Proof} The first claim \( R_\varepsilon(x) + \varepsilon \Delta \in P_{\text{co}}(\delta) \) is obvious by convexity. Under the assumptions we may apply Corollary \[B.5\] to obtain that \( d_H(x, x^\ast) \geq \eta \) implies
\[
\varepsilon^{d_H}(R_\varepsilon(x), x^\ast) < (1 - C_\eta \varepsilon)\varepsilon^{d_H}(x, x^\ast). \tag{98}
\]
Thus with an application of Lemma \[B.6\] we obtain
\[
\varepsilon^{d_H}(R_\varepsilon(x) + \varepsilon \Delta, x^\ast) \leq \varepsilon^{d_H}(R_\varepsilon(x), x^\ast) + K_\delta \leq (1 - \frac{C_\eta}{2})\varepsilon^{d_H}(x, x^\ast) + \varepsilon \left( -\frac{C_\eta}{2} \varepsilon + K \delta \right).
\]
By assumption the last term on the right hand side is negative and we obtain \[96\]. The final claim \[97\] is then obvious. \( \square \)

\textbf{Lemma B.8} Let \( x^\ast \in \Sigma \) be the unique fixed point of \( P \), as described in Lemma \[B.1\]. There exists a constant \( C > 0 \) such that for all \( x, y \in \Sigma \) with \( x \gg 0 \) and for all \( \varepsilon \in [0, 1) \) we have
\[
d_H((1 - \varepsilon)x + \varepsilon y, x^\ast) \leq d_H(x, x^\ast) + \log \left( 1 + C \frac{\varepsilon}{1 - \varepsilon} \right). \tag{99}
\]
In particular, for any \( 0 < \varepsilon_0 < 1 \) there is a constant \( C_0 \) such that for all \( x, y \in \Sigma \) with \( x \gg 0 \) and for all \( \varepsilon \in [0, \varepsilon_0) \) we have
\[
d_H((1 - \varepsilon)x + \varepsilon y, x^\ast) \leq d_H(x, x^\ast) + C_0 \varepsilon. \tag{100}
\]
Proof Let $x, y \in \Sigma$ be arbitrary with $x \gg 0$. Then we obtain
\[
ed^H((1-\varepsilon)x + \varepsilon y, x^*) = \max_i \{(1-\varepsilon)x_i + \varepsilon y_i)/x_i^*\} \leq \max_i \{(1-\varepsilon)x_i + \varepsilon y_i)/x_i^*\} \leq \max_i \{(1-\varepsilon)x_i + \varepsilon y_i)/x_i^*\}
\]
and using that $\max_i \{x_i/x_i^*\} \geq 1$ and $x_i^* \geq x_{\min}^*$ we obtain
\[
\leq \ned^H(x, x^*) \left(1 + \frac{\varepsilon}{1 - \varepsilon} \frac{1}{x_{\min}^*}\right).
\]
The claim (99) now follows by taking the logarithm and defining $C$ appropriately. Then (100) follows as $1/(1 - \varepsilon)$ is bounded on an interval of the form $[0, \varepsilon_0]$ for $\varepsilon_0 < 1$.

C Proof of the Main Result

In the following derivation we will make use of a simple fact concerning sequences of random variables.

Lemma C.1 Let $\{U_k\}_{k \in \mathbb{N}}$ be a sequence of independent, identically distributed, real-valued random variables with well defined expectation $E(U_1) < 0$ and finite variance $\text{VAR}(U_1) \in \mathbb{R}$. Suppose that $\{\varepsilon_k\}_{k \in \mathbb{N}}$ is a sequence of positive real numbers that is square summable, but not summable. Then
\[
\sum_{k=1}^{\ell+L} \varepsilon_k U_k \to -\infty \quad \text{as } L \to \infty \quad \text{a.s.} 
\]  
Furthermore,
\[
\lim_{\ell \to \infty} \sup_{L \geq 0} \sum_{k=\ell}^{\ell+L} \varepsilon_k U_k = 0 \quad \text{a.s.}
\]

Proof Introduce the random sequence $\{V_k\}$ defined by
\[
V_k = \varepsilon_k (U_k - \bar{U}),
\]
where $\bar{U} := E(U_1)$. Then, for all $k$, $\bar{U} = E(U_k)$ and $E(V_k) = 0$. Also, since the second moment of $U_k$ exists, we may compute
\[
\text{VAR}(V_k) = \varepsilon_k^2 \text{VAR}(U_k) = \varepsilon_k^2 \text{VAR}(U_1).
\]
By assumption on the sequence $\{\varepsilon_k\}$ the series $\sum_{k=1}^{\infty} \text{VAR}(V_k)$ converges and so by [5, Theorem 22.6] $\sum_{k=1}^{\infty} V_k$ converges almost surely to a finite value. Since
\[
\varepsilon_k U_k = \varepsilon_k \bar{U} + V_k
\]
we have
\[
\sum_{k=1}^{\ell+L} \varepsilon_k U_k = \left(\sum_{k=1}^{\ell+L} \varepsilon_k\right) \bar{U} + \sum_{k=1}^{\ell+L} V_k
\]
By assumption, the positive sequence $\{\varepsilon_k\}$ is not summable while $\bar{U} < 0$; hence $\sum_{k=1}^{\ell+L} \varepsilon_k U_k$ diverges almost surely to $-\infty$.

To prove the second claim, consider
\[
\sum_{k=\ell}^{\ell+L} \varepsilon_k U_k \leq \sum_{k=\ell}^{\ell+L} \varepsilon_k \bar{U} + \sum_{k=\ell}^{\ell+L} V_k \leq \sum_{k=\ell}^{\ell+L} V_k
\]
Again by [5, Theorem 22.6] the partial sums on the right are almost surely partial sums of a convergent series. Then the Cauchy criterion says that there are only finitely many $\ell \in \mathbb{N}$ such that the sum exceeds a given $C > 0$. This shows "$\leq 0$" in (102). Equality follows from the case $L = 0$. \qed
In the proof we also need a continuity result extending Lemma 2.2 to the family of Markov chains with fixed probability $z_0 \in \Sigma$. In the following result we use the notation $\mathbb{P}_{z_0}$ to indicate a probability statement for the Markov chain $[12]$ with fixed probability $\lambda = \lambda(z_0)$.

**Lemma C.2** Suppose that Assumptions (A1)–(A3) hold. Consider the family of Markov chains $[12]$ with fixed probability $\lambda = \lambda(y)$, parametrized by $y \in \Sigma$. Then, for each $\delta > 0$ and $\theta \in (0,1]$ there exists an $m \in \mathbb{N}$ such that for all $y \in \Sigma$

$$\hat{\mathbb{P}}_{\lambda(y)} (\| \hat{S}(m) - P(y)e^\top \|_1 > \delta) < \theta. \quad (104)$$

**Proof** Fix $\varepsilon, \delta > 0$ and $\hat{y} \in \Sigma$. By Lemma 2.2 there exists an $\hat{m}$ such that

$$\hat{\mathbb{P}}_{\lambda(\hat{y})} (\| \hat{S}(\hat{m}) - P(\hat{y})e^\top \|_1 > \delta) < \varepsilon. \quad (105)$$

Now the map $P$ is continuous by Assumptions (A1) and (A3). Furthermore, the map

$$y \rightarrow \hat{\mathbb{P}}_{\lambda(y)} (\| \hat{S}(\hat{m}) - P(\hat{y})e^\top \|_1 > \delta)$$

is continuous. We obtain that

$$\hat{\mathbb{P}}_{\lambda(y)} (\| \hat{S}(\hat{m}) - P(y)e^\top \|_1 > 2\delta) < 2\varepsilon. \quad (106)$$

holds on a neighborhood of $\hat{y}$. As $\Sigma$ is compact, it is covered by a finite number of such neighborhoods. With this argument, and as $\varepsilon, \delta$ are arbitrary, we see that there are finitely many $\hat{m}_1, \ldots, \hat{m}_N$ in $\mathbb{N}$ such that for every $y \in \Sigma$ there is an $\hat{m}_j$ such that $(105)$ holds with $\hat{m} = \hat{m}_j$.

The final claim then follows from an application of Tchebycheff’s inequality as follows. For $y \in \Sigma$ and $k \in \mathbb{N}$ consider the real valued random variable

$$D(k) = \| \hat{S}(k) - P(y)e^\top \|_1.$$ 

Note that $0 \leq D(k) \leq 2$, as $\hat{S}(k)$ and $P(y)e^\top$ are column stochastic. Thus trivially, $\mathbf{E}(D(k)^2) \leq 4$. Also, if $(105)$ holds then it follows that

$$\mathbf{E}(D(\hat{m})) \leq (1 - \varepsilon)\delta + 2\varepsilon. \quad (107)$$

We note that the latter inequality is independent of a particular $y$ and just depends on the fact that $\hat{m}$ is chosen so that $(105)$ holds. Fix $\delta, \theta > 0$. Suppose that $\varepsilon, \delta > 0$ are chosen such that $(1 - \varepsilon)\delta + 2\varepsilon < 3/2$. Then it follows from $(105)$ that

$$\mathbf{E}(D(\hat{m})) < \frac{3}{2}. \quad (106)$$

Denoting

$$\Pi(k) = A(k-1)\cdots A(0)$$

for $k \in \mathbb{N}$, we have

$$\hat{S}(k) = \frac{1}{k+1} \sum_{j=0}^{k} \Pi(j).$$

Hence, for multiples of $\hat{m}$:

$$\hat{S}(\ell \hat{m}) = \frac{1}{\ell \hat{m} + 1} \sum_{i=1}^{\ell \hat{m}} \Pi(i) = \frac{1}{\ell \hat{m} + 1} \sum_{\nu=0}^{\ell-1} \sum_{j=0}^{\hat{m}-1} \Pi(\nu \ell + j)$$

$$= \frac{1}{\ell \hat{m} + 1} \sum_{\nu=0}^{\ell-1} \sum_{j=0}^{m-1} A(\nu \ell + j) \cdots A(\nu \ell) \Pi(\nu \ell).$$
Appendix B. We will show that for

\[ \text{We assume that the constants} \]

\[ \text{deterministic system.} \]

Proof (of Theorem 4.6)

which the choice of

\[ \text{resp.} \]

\[ \text{As the previous argument only depends on the validity of (105), it holds uniformly for all} \]

\[ \text{By the independence assumption on the} \]

\[ \text{Fix} \]

\[ \text{To attain our goal, we perform the following sequence of choices:} \]

(i) For the constant \( \eta > 0 \) and \( C_\eta > 0 \) according to Corollary B.5, so that (102) is satisfied for all \( 0 < \epsilon < \epsilon_0 \).

(ii) Let \( C_0 \) be the constant guaranteed by Lemma B.8, satisfying (100) for all \( 0 < \epsilon < \epsilon_0 \).

(iii) Let \( K > 0 \) be the constant given by Lemma B.6.

(iv) Choose \( \delta^*, \bar{\delta} \) according to (95), so that

\[ \delta^* := \min \left\{ \frac{C_\eta \epsilon^2}{2K}, \delta^- \right\} \quad \text{and} \quad 0 < \bar{\delta} < \delta^*/3, \]

so that Corollary B.7 and Lemma B.2(iii) are applicable. Let \( C_\delta > 0 \) be the constant guaranteed by Lemma B.2(iii).

(v) Pick \( \theta \in (0, 1) \) so that

\[ -(1 - \theta) + \theta(1 + C_\delta) < 0, \quad \text{and} \quad -(1 - \theta)C_\eta + \theta C_0 < 0. \]

(vi) We now appeal to Lemma C.2 to determine the length of the (short) averaging period discussed in the preamble.
Using Lemma [C.2] and [20], pick \( m \in \mathbb{N} \) such that for all \( y \in \Sigma \) the Markov chain (12) with fixed probability \( \lambda = \lambda(y) \) satisfies for all \( T \in \mathbb{N} \) that
\[
\mathbb{P}_{\lambda(y)} \left( \left\| \frac{1}{m} \sum_{j=1}^{m} x(T+j) - P(y) \right\|_1 > \delta \right) < \frac{\theta}{2}.
\] (108)

(vii) Pick \( T_0 \in \mathbb{N} \) such that for all \( T \geq T_0 \) we have \( m/(T+m) < \varepsilon_0 \) and so that for the Markov chain (49) with place dependent probabilities we have that
\[
\mathbb{P}_{x_0} \left( \left\| \frac{1}{m} \sum_{j=1}^{m} x(T+j) - P(\bar{x}(T)) \right\|_1 > \delta \right) < \theta.
\] (109)

This is possible as this inequality is a perturbed version of (108): indeed, with increasing \( T \) the variation of \( \bar{x}(T+j), 0 \leq j \leq m \) (i.e. in the first \( m \) steps after time \( T \)) becomes arbitrarily small. More precisely, for \( j = 1, \ldots, m \) we have by definition
\[
||\bar{x}(T) - \bar{x}(T+j)||_1 \leq \frac{2m}{T}.
\]

Thus as \( T \to \infty \) the place dependent probabilities of the Markov chain (49) that are considered on the interval \([T, T+m]\) converge to the fixed probabilities \( \lambda(\bar{x}(T)) \). The claim then follows from (108) by continuity of the probability functions \( \lambda_i \) (see (A1)).

Let \( T \geq T_0 \), so that by construction \( \varepsilon := m/(T+m) < \varepsilon_0 \). We will study the evolution of the value \( \bar{x}(T+km) \to \bar{x}(T+(k+1)m), k \in \mathbb{N} \). This is given by
\[
\bar{x}(T+(k+1)m) = \frac{T+km+1}{T+(k+1)m+1} \bar{x}(T+km) + \frac{m}{T+(k+1)m+1} \left( \frac{1}{m} \sum_{j=1}^{m} x(T+km+j) \right).
\]

For ease of notation we define
\[
\tau(k) := T+km \quad \text{and} \quad \varepsilon_k := \frac{m}{T+(k+1)m+1}
\]
so that the previous equation can be expressed as
\[
\bar{x}(\tau(k+1)) = (1 - \varepsilon_k) \bar{x}(\tau(k)) + \varepsilon_k \left( \frac{1}{m} \sum_{j=1}^{m} x(\tau(k) + j) \right).
\] (110)

At this point the reader should recognize the structure of the discrete iteration we have analyzed in Section B and notice that by (vii) we have a high probability that \( \bar{x}(\tau(k+1)) \) is close to \( R_{\varepsilon_k}(\bar{x}(\tau(k))) \).

Note that the constants have been chosen so that both Lemma [B.2] and Corollary [B.7] are applicable. We will use the estimates obtained in Lemma [B.2] to show that trajectories starting in \( \Sigma \) will reach the set \( P_{\varepsilon}(2\delta) \) in a finite number of steps. We then show that for trajectories starting in the strict supersets \( P_{\varepsilon}(3\delta) \) the estimates of Corollary [B.7] yield that we reach the set \( B_H(x^*, \eta) \) again in a finite number of steps; almost surely.

**Step 1:** More precisely, we will first show that (the first hitting time)
\[
\sigma_1 := \min\{k \in \mathbb{N} : \bar{x}(\tau(k)) \in P_{\varepsilon}(2\delta) \}
\]
is almost surely finite. Obviously, if \( \bar{x}(T) \in P_{\varepsilon}(2\delta) \) there is nothing to show. Appealing to Lemma [B.2] (i) and the choice made in (vii), we have that if \( \text{dist}_1(\bar{x}(\tau(k)), P_{\varepsilon}(\delta)) > \delta \), then
\[
\mathbb{P}_{x_0} \left( \text{dist}_1(\bar{x}(\tau(k+1)), P_{\varepsilon}(\delta)) \leq (1 - \varepsilon_k) \text{dist}_1(\bar{x}(\tau(k)), P_{\varepsilon}(\delta)) \right) \geq 1 - \theta.
\]

\(^6\)This chain is not a typical stochastic approximation chain due to the interdependence between \( x \) and \( \bar{x} \)—cf. [19]. It is similar in form to the two-timescales process of [6], Chapter 6, but does not satisfy the convergence conditions therein.
In the complementary event, which happens with probability of at most \( \theta \) we have by Lemma \[B.2\] that
\[
\text{dist}_1(\bar{x}(\tau(k+1)), \mu_{\theta}(\bar{\delta})) \leq (1 + \varepsilon_k C_\delta) \text{dist}_1(\bar{x}(\tau(k)), \mu_{\theta}(\bar{\delta}))
\]
Combining these two observations we see that for \( \tau(k) < \sigma_1 \) we have that
\[
\text{dist}_1(\bar{x}(\tau(k)), \mu_{\theta}(\bar{\delta})) \leq \left( \prod_{\ell=1}^{k} a_\ell \right) \text{dist}_1(\bar{x}(T), \mu_{\theta}(\bar{\delta})),
\]
where \( a_\ell, \ell \in \mathbb{N} \) is a random variable that has the value \((1 - \varepsilon_\ell)\) with probability \( 1 - \theta \) and the value \((1 + \varepsilon_\ell C_\delta)\) with probability \( \theta \). By construction the random variables \( a_\ell \) are independent, as the bounds obtained do not depend on the particular sample path of the Markov chain.

To be able to apply Lemma \[C.1\] we first note that for all \( \ell \) large enough we have \( \log(1 + \varepsilon_\ell C_\delta) \leq \varepsilon_\ell (1 + C_\delta) \).

By the choice of \( \varepsilon_\ell \) in (vi), we obtain for all \( \ell \) large enough that \( \mathbb{E}(\log a_\ell) \leq (- (1 - \theta) + \theta (1 + C_\delta)) \varepsilon_\ell \). Lemma \[C.1\] thus implies that \( \sum_{\ell=1}^{k} \log a_\ell \to - \infty \), almost surely. Thus almost surely we have
\[
\lim_{k \to \infty} \text{dist}_1(\bar{x}(\tau(k)), \mu_{\theta}(\bar{\delta})) = 0,
\]
provided that \( \bar{x}(\tau(k)) \notin \mu_{\theta}(2\bar{\delta}) \) for all \( k \). This is of course impossible, and so almost surely \( \bar{x}(\tau(k)) \in \mu_{\theta}(2\bar{\delta}) \) for a finite \( k \).

**Step 2:** Similarly, if \( \bar{x}(\tau(k)) \in \mu_{\theta}(3\bar{\delta}) \), then by Corollary \[B.7\] and the choice made in (vii) we have
\[
\mathbb{P}_{x_0} \left( d_H(\bar{x}(\tau(k+1)), x^*) < d_H(\bar{x}(\tau(k)), x^*) - \frac{C_\eta}{2} \varepsilon_k \right) \geq 1 - \theta.
\]
On the other hand with probability of at most \( \theta \) we have by Lemma \[B.8\] that
\[
d_H(\bar{x}(\tau(k+1)), x^*) \leq d_H(\bar{x}(\tau(k)), x^*) + C_0 \varepsilon_k.
\]
In a similar fashion to the first step, as long as \( \bar{x}(\tau(k)) \in \mu_{\theta}(3\bar{\delta}) \) and \( d_H(\bar{x}(\tau(k)), x^*) > \eta \), we have
\[
d_H(\bar{x}(\tau(\sigma_1(\bar{T}(k) + k)), x^*) \leq d_H(\bar{x}(\sigma_1(\bar{T}(k) + k)), x^*) + \sum_{\ell=1}^{k} b_\ell,
\]
where \( b_\ell \) is a random variable that takes the value \(- \varepsilon_\ell C_\eta \) with probability \( 1 - \theta \) and the value \( \varepsilon_\ell C_\theta \) with probability \( \theta \). As before, Lemma \[C.1\] ensures that \( \sum_{\ell} b_\ell \) diverges to \(- \infty \), almost surely. Note that it is always possible to leave the set \( \mu_{\theta}(3\bar{\delta}) \) with a small probability. In this case Step 1 can be applied again, so that we re-enter the set \( \mu_{\theta}(2\bar{\delta}) \), almost surely. Now by (111) the process of entering \( \mu_{\theta}(2\bar{\delta}) \) and subsequently leaving \( \mu_{\theta}(3\bar{\delta}) \) requires that for some partial sum we have
\[
\sum_{k=\ell}^{\ell+L} \log(a_k) \geq \bar{\delta}.
\]
By Lemma \[C.1\] with probability 1, this happens only a finite number of times. Consequently, almost surely a sample path will reach \( B_H(x^*, \eta) \).

**Step 3:** Finally, to obtain almost sure convergence, we need to show that almost surely
\[
\bar{x}(\tau(k)) \in B_H(x^*, \eta), \quad \text{for all } k \text{ large enough.}
\]
To this end we repeat the choices made in (i) - (vii) for the value \( \eta/2 \). Thus we can conclude that almost surely a sample path enters \( B_H(x^*, \eta/2) \). If we assume that the sample path leaves \( B_H(x^*, \eta) \) at some later time, then again by Steps 1 and 2 it will almost surely re-enter \( B_H(x^*, \eta/2) \). The question is thus whether it is possible that infinitely often the sample path exits the ball \( B_H(x^*, \eta) \) given that it was previously within the ball \( B_H(x^*, 3\eta/4) \). In view of (113) this amounts to saying that
\[
\sum_{k=\ell}^{\ell+L} b_k > \frac{\eta}{4}
\]
for pairs \((\ell, L) \in \mathbb{N}^2\) with arbitrarily large \(\ell\). By Lemma C.1 this almost surely does not happen. This shows \([14]\). The proof is complete by noting that the small variations of \(\bar{x}\) on the intervals \(\tau(k), \ldots, \tau(k+1)\) do not destroy stability. Indeed, if \(\bar{x}(\tau(k)) \in B_H(x^*, \eta/2)\) for all \(k\) large enough, then also \(\bar{x}(\tau(k) + j) \in B_H(x^*, \eta)\) for \(j = 1, \ldots, m\), provided \(k\) is large enough. \(\square\)

D Acknowledgment

The authors thank Ronald Fagin for helpful comments on an earlier version of this paper.

References

[1] D. Angeli and P.-A. Kountouriotis. A stochastic approach to dynamic-demand refrigerator control. *IEEE Transactions on Control Systems Technology*, 20(3):581–592, May 2012.

[2] M. Barnsley, S. Demko, J. Elton, and J. Geronimo. Invariant measures for Markov processes arising from iterated function systems with place-dependent probabilities. *Annales de l’Institut Henri Poincaré (B) Probabilités et Statistiques*, 24(3):367–394, 1988.

[3] P. Bianchi, G. Fort, and W. Hachem. Performance of a distributed stochastic approximation algorithm. *IEEE Transactions on Information Theory*, 59(11):7405–7418, Nov 2013.

[4] B. Biegel, P. Andersen, T. Pedersen, K. Nielsen, J. Stoustrup, and L. Hansen. Smart grid dispatch strategy for ON/OFF demand-side devices. In *2013 European Control Conference (ECC)*, pages 2541–2548, Zurich, Switzerland, July 2013. IEEE.

[5] P. Billingsley. *Probability and Measure*. John Wiley & Sons, Hoboken, NJ, 1995. 3rd ed.

[6] V. S. Borkar. *Stochastic Approximation: A Dynamical Systems Viewpoint*. Cambridge University Press, Cambridge, UK, 2008.

[7] S. Boyd and L. Vandenberghe. *Convex Optimization*. Cambridge University Press, New York, NY, USA, 2004.

[8] A. Brooks, E. Lu, D. Reicher, C. Spirakis, and B. Weihl. Demand dispatch. *IEEE Power and Energy Magazine*, 8(3):20 – 29, May - June 2010.

[9] M. Chiang, S. Low, R. Calderbank, and J. Doyle. Layering as optimization decomposition: A mathematical theory of network architectures. *Proceedings of IEEE*, 95(1):255–312, 2007.

[10] K. Clement, E. Haesen, and J. Driesen. Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids. In *IEEE/PES Power Systems Conference and Exposition (PSCE)*, pages 1 – 7, Seattle, WA, March 2009. IEEE.

[11] K. Clement-Nyns, E. Haesen, and J. Driesen. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Transactions on Power Systems*, 25(1):371 – 380, February 2010.

[12] M. Corless, C. King, R. Shorten, and F. Wirth. *AIMD Dynamics and Distributed Resource Allocation*. Number 29 in Advances in Design and Control. SIAM, Philadelphia, PA, 2016.

[13] M. Corless and R. Shorten. Analysis of a general nonlinear increase resource allocation algorithm with application to network utility maximization. submitted, March 2014.

[14] E. Crisostomi, M. Liu, M. Raugi, and R. Shorten. Stochastic distributed algorithms for power generation in a microgrid. *IEEE Transactions on Smart Grid*, 5(4):2145–2154, 2014.

[15] S. Deilami, A. Masoum, P. Moses, and M. Masoum. Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile. *IEEE Transactions on Smart Grid*, 2(3):456 – 467, September 2011.
[16] J. Duchi, A. Agarwal, and M. Wainwright. Dual averaging for distributed optimization: Convergence analysis and network scaling. *IEEE Transactions on Automatic Control*, 57(3):592–606, 2012.

[17] J. H. Elton. An ergodic theorem for iterated maps. *Ergodic Theory Dynam. Systems*, 7(4):481–488, 1987.

[18] L. P. Fernández, T. S. Róman, R. Cossent, C. Domingo, and P. Frías. Assessment of the impact of plug-in electric vehicles on distribution networks. *IEEE Transactions on Power Systems*, 26(1):206–213, February 2011.

[19] P. Finn, C. Fitzpatrick, and M. Leahy. Increased penetration of wind generated electricity using real time pricing; demand side management. In *IEEE International Symposium on Sustainable Systems and Technology (ISSST)*, pages 1–6, Tempe, AZ, May 2009. IEEE.

[20] S. Floyd. High speed TCP for large congestion windows. Technical report, Internet draft draft-floyd-tcp-highspeed-02.txt, work in progress, February 2003.

[21] A. Harris. Charge of the electric car [electric vehicles]. *Engineering and Technology*, 4(10):52–53, June 2000.

[22] D. J. Hartfiel. *Nonhomogeneous Matrix Products*. World Scientific, Singapore, 2002.

[23] V. Jacobson. Congestion avoidance and control. *ACM SIGCOMM Computer Communication Review*, 18(4):314–329, 1988.

[24] B. Johansson, M. Rabi, and M. Johansson. A randomized incremental subgradient method for distributed optimization in networked systems. *SIAM Journal on Control and Optimization*, 49(3):1157–1170, 2009.

[25] R. Johari and J. N. Tsitsiklis. Efficiency loss in a network resource allocation game. *Mathematics of Operations Research*, 29(3):407–435, 2004.

[26] K. Kar, S. Sarkar, and L. Tassiulas. A simple rate control algorithm for max total user utility. In *Proc. 2001 IEEE INFOCOM, Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies*, volume 1, pages 133–141 vol.1, Anchorage, AL, 2001. IEEE.

[27] T. Kelly. On engineering a stable and scalable TCP variant. Technical report, Cambridge University Engineering Department Technical Report CUED/F-INFENG/TR.435, 2002.

[28] S. Kumar, S.-J. Park, and S. Sitharama Iyengar. A loss-event driven scalable fluid simulation method for high-speed networks. *Computer Networks*, 54(1):112–132, 2010.

[29] S. Kunniyur and R. Srikant. End-to-end congestion control schemes: Utility functions, random losses and ECN marks. *IEEE/ACM Transactions on Networking*, 11(5):689–702, 2003.

[30] N. Li, L. Chen, and S. Low. Optimal demand response based on utility maximization in power networks. In *2011 IEEE Power and Energy Society General Meeting*, pages 1–8, Detroit, MI, July 2011. IEEE.

[31] S. Low, F. Paganini, and J. Doyle. Internet congestion control. *IEEE Control Systems Magazine*, 32(1):28–43, 2002.

[32] S. H. Low, L. L. Peterson, and L. Wang. Understanding TCP Vegas: a duality model. *Journal of the ACM (JACM)*, 49(2):207–235, 2002.

[33] G. Mann, R. T. McDonald, M. Mohri, N. Silberman, and D. Walker. Efficient large-scale distributed training of conditional maximum entropy models. *Advances in Neural Information Processing Systems*, 22:1231–1239, 2009.

[34] J. Masaki, G. Nishantha, and Y. Hayashida. Development of a high-speed transport protocol with TCP-Reno friendliness. In *International Conference on Advanced Communication Technology, ICACT*, volume 1, pages 174–179, Republic of Korea, 2010.
[35] J. Mathieu, M. Kamgarpour, J. Lygeros, and D. Callaway. Energy arbitrage with thermostatically controlled loads. In 2013 European Control Conference (ECC), pages 2519–2526, Zurich, Switzerland, July 2013. IEEE.

[36] S. Molnar, S. Balazs, and T. Tuan. A comprehensive TCP fairness analysis in high speed networks. Computer Communications, 32:1460–1484, 2009.

[37] A. Nedic and A. Ozdaglar. Distributed subgradient methods for multi-agent optimization. IEEE Transactions on Automatic Control, 54(1):48–61, 2009.

[38] G. Putrus, P. Suwanapingkarl, D. Johnston, E. Bentley, and M. Narayana. Impact of electric vehicles on power distribution networks. In IEEE Vehicle Power and Propulsion Conference (VPPC), pages 827–831, Dearborn, MI, September 2009. IEEE.

[39] S. S. Ram, A. Nedić, and V. V. Veeravalli. Distributed stochastic subgradient projection algorithms for convex optimization. Journal of Optimization Theory and Applications, 147(3):516–545, 2010.

[40] U. G. Rothblum and R. Shorten. Nonlinear aimd congestion control and contraction mappings. SIAM Journal on Control and Optimization, 46(5):1882–1896, 2007.

[41] S. Sayeef, S. Heslop, D. Cornforth, T. Moore, S. Percy, J. K. Ward, A. Berry, and D. Rowe. Solar intermittency: Australia’s clean energy challenge, June 2012. accessed at "http://www.csiro.au/Organisation-Structure/Flagships/Energy-Flagship/Solar-Intermittency-Report.aspx" on 5.3.2014.

[42] S. Shafiei, H. Rasmussen, and J. Stoustrup. Model predictive control for a thermostatic controlled system. In 2013 European Control Conference (ECC), pages 1559–1564, Zurich, Switzerland, July 2013. IEEE.

[43] R. Shorten, C. King, F. Wirth, and D. Leith. Modelling TCP congestion control dynamics in drop-tail environments. Automatica, 43(3):441–449, 2007.

[44] R. Shorten, F. Wirth, and D. Leith. A positive systems model of TCP-like congestion control: Asymptotic analysis. IEEE/ACM Transactions on Networking, 14:616–629, 2006.

[45] R. Srikant. Internet Congestion Control, volume 14 of Control Theory. Birkhäuser Boston Inc., Boston, MA, 2004.

[46] R. Stanojevic and R. Shorten. Distributed dynamic speed scaling. In Proc. 2010 IEEE INFOCOM, pages 1–5, San Diego, CA, March 2010. IEEE.

[47] S. Stuedli, E. Crisostomi, R. Middleton, and R. Shorten. A flexible distributed framework for realising electric and plug-in hybrid vehicle charging policies. International Journal of Control, 85(8):1130 – 1145, 2012.

[48] K. Tan, J. Song, Q. Zhang, and M. Sridharan. A compound TCP approach for high-speed and long distance networks. In Proc. 25th IEEE INFOCOM, pages 1–12, 2006.

[49] F. Wirth, R. Stanojevic, R. Shorten, and D. Leith. Stochastic equilibria of AIMD communication networks. SIAM Journal on Matrix Analysis and Applications, 28(3):703–723, 2006.

[50] L. Xu, K. Harfoush, and I. Rhee. Binary increase congestion control (BIC) for fast long-distance networks. In Proc. of IEEE INFOCOM 2004, pages 2514–2524, Hong Kong, 2004. IEEE.

[51] J. Y. Yu and S. Mannor. Asymptotics of efficiency loss in competitive market mechanisms. In Proc. 25th IEEE INFOCOM, pages 1–13, Barcelona, Spain, 2006. IEEE.

[52] M. Zinkevich, M. Weimer, A. J. Smola, and L. Li. Parallelized stochastic gradient descent. Advances in Neural Information Processing Systems, 23:2595–2603, 2010.