Optimization-Based Predictive Congestion Control for the Tor Network: Opportunities and Challenges

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Based on the principle of onion routing, the Tor network achieves anonymity for its users by relaying user data over a series of intermediate relays. This approach makes congestion control in the network a challenging task. As of this writing, this results in higher latencies due to considerable backlog as well as unfair data rate allocation. In this article, we present a concept study of PredicTor, a novel approach to congestion control that tackles clogged overlay networks. Unlike traditional approaches, it is built upon the idea of distributed model predictive control, a recent advancement from the area of control theory. PredicTor is tailored to minimizing latency in the network and achieving max-min fairness. We contribute a thorough evaluation of its behavior in both toy scenarios to assess the optimizer and complex networks to assess its potential. For this, we conduct large-scale simulation studies and compare PredicTor to existing congestion control mechanisms in Tor. We show that PredicTor is highly effective in reducing latency and realizing fair rate allocations. In addition, we strive to bring the ideas of modern control theory to the networking community, enabling the development of improved, future congestion control. Thus, we demonstrate benefits and issues alike with this novel research direction.

CCS Concepts: • Networks → Overlay and other logical network structures; Network performance analysis; Transport protocols; Network privacy and anonymity; Network simulations; • Security and privacy → Pseudonymity, anonymity and untraceability;

Additional Key Words and Phrases: Tor network, multi-hop congestion control, model predictive control

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1 INTRODUCTION

In today’s digital society, protecting Internet privacy has become more important than ever. The growing demand for online anonymity has resulted in advanced technical solutions to satisfy this need. With around 2.2 million daily users [38], the Tor network [13] is currently by far the most widely used anonymization network. Tor builds upon the idea of onion routing [17]. It consists of an overlay network connecting so-called relay nodes, which can be used to establish anonymous connections. To this end, the Tor client software builds a cryptographically secured circuit, a path over three relays, where each relay knows its immediate neighbors only.

This has several performance implications. Due to re-routing the traffic multiple times through the overlay network, an extra delay is inevitable to gain anonymity. However, the performance—in terms of latency, data rates, and fairness—is suboptimal [12, 35]. One of the major shortcomings is the lack of effective congestion control [1, 12], which minimizes network load and optimizes the user-perceivable performance. While congestion control is a nontrivial task even for single connections, relaying data over a series of nodes, like in Tor, amplifies the problem, especially when rising delays occur in the network. In particular, Tor relays are unable to react to congestion, for example, by signaling upstream to throttle sending rates. Moreover, a growing demand for the Tor network will also result in a growing need for effective congestion control to satisfy the users’ expectations as far as latency, throughput, and fairness are concerned. Therefore, one also has to consider novel research approaches to meet these challenges.

With PredicTor [16], we introduce a new research direction towards congestion control in multi-hop overlay networks like the Tor network. PredicTor is the first system to apply distributed Model Predictive Control (MPC) [30] to congestion control in the Tor network. MPC in general is a modern technique from the field of control theory that uses predictions about the future system state as well as the repeated solving of a formal optimization problem to achieve optimal behavior. Predictions are deduced from a mathematical system model that is instantiated with real-world measurements. For applying MPC in the context of multi-hop congestion control, we distribute it among relays. That is, each relay solves the optimization problem with its local view of the network, but controllers cooperate by exchanging their predictions to establish network-wide behavior. In contrast to the current behavior of Tor, PredicTor avoids congestion by generating backpressure. By relying on a formal definition of the optimization goal, it becomes possible to optimize the congestion control within the network for specific optimization objectives. In PredicTor, we put a special emphasis on low latency and fairness in the network, because these have previously been identified to be especially problematic in the Tor network [35, 41]. While optimization-based rate allocation has been researched before, with equivalent formulations for TCP and other methods [18], we introduce a novel optimization-based max-min fairness formulation.

In addition to presenting PredicTor, the goal of this article is to bring the underlying control-theoretic approach to the network community. We pinpoint the merits and the potential of applying distributed MPC to congestion control but also point out current shortcomings. Our work should be understood as a concept study for this novel field rather than a ready-to-deploy finished technical solution. We envision opening up new directions and fostering the development of novel, innovative techniques for congestion control. Our evaluation reveals that PredicTor is able to clearly reduce latency: In a small model scenario, it achieves a latency reduction from 553 ms (vanilla Tor) to 94 ms. In larger, random networks, the advantage becomes even more apparent because, in contrast to traditional approaches, latency does not significantly grow with growing congestion. At the same time, PredicTor consistently realizes near-perfect max-min fairness. However, we show that this comes at the cost of lower throughput and more signaling overhead.

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The term “controller” refers to the local application of control techniques. It does not imply a centralized entity.
The contributions are summarized as follows.

- We introduce PredicTor for congestion control in the Tor network based on distributed MPC. Compared with [16], we add an important change to its optimization problem that strengthens its robustness.
- We present a novel, optimization-based formulation of max-min fairness and leverage it as an optimization goal in PredicTor.
- We implement a prototype of PredicTor to enable experimental assessment of its behavior. Our implementation is made available as an open source software project.²

PredicTor was first introduced in [16]. In this journal article, we especially focus on PredicTor’s significance for networking research by covering the following additional aspects.

- We introduce optimization-based predictive congestion control to the networking community.
- We discuss possible security and privacy implications of PredicTor.
- We provide a simulation study of PredicTor’s performance in complex network scenarios, analyzing whether its optimization goals can be realized in non-trivial environments.
- We leverage the results and a thorough investigation of PredicTor’s underlying assumptions to identify the benefits and potential drawbacks of this new approach towards congestion control.

This article is structured as follows. We start by presenting the preliminaries for our approach, including related terminology and mathematical notation, in Section 2. Section 3 introduces PredicTor itself in full detail, including our novel optimization-based method for obtaining max-min fairness and the dynamic system model. We discuss security and privacy implications of PredicTor in Section 4. In Section 5, we present our evaluation of PredicTor, focusing first on small scenarios to demonstrate its functioning before we leverage larger-scale simulations of complex networks for deeper insights. In this section, we also discuss the implications for further research on congestion control using MPC. We complete our work by presenting related work in Section 6 and summarizing this contribution in Section 7.

2 PRELIMINARIES

2.1 The Tor Network

In the face of today’s growing need for online privacy, Tor provides an essential tool for applications that require anonymity on the Internet. It is an overlay network that makes use of the principle of onion routing [17]. It achieves anonymity by tunneling users’ data through the network, over a series of relays, called a circuit. Onion routing ensures that each hop in the relay knows only its immediate predecessor and successor. As a consequence, destinations cannot identify the origin of streams of communication that they receive. Clients typically choose a sequence of three random relays for constructing a circuit. The necessary resources (service and bandwidth) are contributed by volunteers and are not subject to a central authority.

More formally, we introduce Tor as an overlay network graph $G(N, E)$, where $N$ denotes the set of nodes and $E$ the set of overlay links. The network has a total of $|N| = n$ nodes and $|E| = e$ connections. We denote the set of Tor circuits $P$ with $i \in P$ being the i-th circuit of the set of cardinality $|P| = p$. $P_\alpha \in P$ denotes the subset of circuits traversing node $\alpha \in N$. Generally, we refer to circuits with Roman letters and to nodes with Greek letters. When considering the network at the circuit level, we denote the data rate of circuit $i$ with $r_i$ (in packets per second). Furthermore,
Each node $\alpha \in N$ of the overlay network has a limited capacity $C_\alpha$, since overlay connections share the same physical connection. Each node $\alpha \in N$ can receive, store, and send data from each circuit $i \in P_\alpha$. We denote $s_{\alpha,i}$ the circuit queue (storage in number of packets) in node $\alpha$ for circuit $i$ and the vector with all queues for each circuit in node $\alpha$ as $s_{\alpha} \in \mathbb{N}^{|P_\alpha|}$.

A useful metric to measure the congestion in the network is given by the backlog that captures the amount of data that is on its way through the network. In terms of our formal description, we define it as follows:

**Definition 1.** The data backlog $b$ of a network $G(N, E)$ is computed for all nodes $\alpha \in N$ and all circuits $i \in P$ as

$$b = \sum_{\alpha \in N} \sum_{i \in P} s_{\alpha,i}. \quad (1)$$

In various sections of this article, we focus on a small example topology of circuits, depicted in Figure 1. It consists of two sending relays that carry three circuits, whose traffic streams meet in a shared node, constituting a bottleneck. Then, the three circuits go to distinct destination relays. We found this simple topology to be useful for evaluating the behavior of congestion control in Tor because it represents a typical situation in which a single relay is overloaded by several circuits. The scenario is still simple enough to understand the decisions made by congestion control.

### 2.2 Fairness

When considering performance in networks, the immediate measures that come into mind are throughput and latency. However, another important metric is fairness. Especially in overlay networks such as Tor, in which many data transfers compete for the available resources, fairness is important to guarantee an adequate user experience to the majority of users. Different fairness measures have been put forward [7]. Here, we focus on the strong notion of *max-min fairness* as it has been proposed as the fairness goal for the Tor network. To define it formally, we first introduce the notion of *feasibility*—that is, distributions of data rates that can actually be realized in the network [7].

**Definition 2.** A rate vector $r = [r_1, r_2, \ldots, r_p]$ is feasible if

$$\forall i \in P : 0 \leq r_i \quad \text{and}$$

$$\forall \alpha \in N : \sum_{i \in P_\alpha} r_i \leq C_\alpha. \quad (3)$$

We denote $R_f$ the set of feasible rate vectors.
This allows us to define max-min fairness as follows:

**Definition 3.** A feasible rate vector \( r_f \in R_f \) is called max-min fair if for all circuits \( i \in P \) and for all other feasible rates \( \bar{r} \in R_f \) it holds that

\[
\bar{r}_i \geq r_f^i \Rightarrow \exists j \in P : r_f^j \leq r_f^i \wedge \bar{r}_j \leq r_f^j.
\]

This definition means that if a rate \( r_f \) is max-min fair, any other feasible rate that increases the rate for the favored circuit \( i \) comes at the cost of reducing the rate for the disadvantaged circuit \( j \), which is already smaller than the rate of circuit \( i \).

### 2.3 Model Predictive Control

In this subsection, we briefly review the concept of MPC, which is used to formulate our proposed congestion controller. Fundamental for this approach is the notion of a dynamic system:

\[
x^{k+1} = f(x^k, u^k, p^k),
\]

which relates a state \( x^k \in \mathbb{R}^n \), input \( u^k \in \mathbb{R}^m \), and parameter \( p^k \in \mathbb{R}^p \) at sampling time \( k \) to the state at the next sampling time \( k + 1 \). Under the assumption that the model \( f(x^k, u^k, p^k) \) accurately describes the system, Equation (5) can be used to compute the future states of the system given the initial state, sequence of inputs, and parameters. Based on the dynamic system in Equation (5), we introduce the finite horizon optimal control problem (OCP):

\[
\begin{align*}
\min_{u, x} & \quad \sum_{k=0}^{N_{\text{horz}}} l(x^k, u^k, p^k) \\
\text{subject to:} & \quad x^{k+1} = f(x^k, u^k, p^k), \\
& \quad g(x^k, u^k, p^k) \leq 0 \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad x^0 = x_{\text{init}}.
\end{align*}
\]

In this problem, we are optimizing over finite sequences of inputs \( u = [u^0, \ldots, u^{N_{\text{horz}}}] \) and states \( x = [x^0, \ldots, x^{N_{\text{horz}}+1}] \). The optimal solution is obtained for a given initial state \( x_{\text{init}} \) and a sequence of parameters \( p = [p^0, \ldots, p^{N_{\text{horz}}}] \). We use bold letters to denote trajectories. The objective is to minimize an arbitrary cost function under the consideration of additional constraints. Typically, this cost function consists of individual contributions for each step of the horizon, as shown in Equation (6a). The previously introduced dynamic system in Equation (5) is considered in Equation (6b) as an equality constraint. Additionally, we have in Equation (6c) inequality constraints on states and inputs, possibly under consideration of the parameters. This possibility to explicitly formulate constraints is a major advantage of MPC over alternative advanced control techniques.

As the solution of the OCP (see Equation (6)), we obtain the predicted future sequence of states and the respective sequence of inputs. For the control application, the first element of the sequence of inputs, that is, \( u^0 \), is applied to the system, typically in the form of a constant value over a finite sampling time. After this sampling time, the new state of the system is obtained and, together with the updated sequence of parameters problem, the OCP in Equation (6) is solved again. Feedback through this closed-loop application allows robust reaction to disturbances and mitigates potential mismatches between model and controlled systems.

MPC is also a popular method to deal with distributed control systems. In this application, multiple controllers make local decisions and attempt to achieve global control goals by...
communicating their decisions. In particular, the distributed MPC controllers can exchange their predicted future states and inputs that are obtained as a by-product when computing the current input to the system. Connected controllers can consider this information as the additional parameters in Equation (6). Knowledge over future actions of connected controllers has the significant advantage that the effect of delay can be mitigated.

3 PREDICTOR

In this section, we introduce PredicTor, our newly proposed congestion controller for the Tor network. PredicTor is developed with the following objectives in mind. Primarily, we are aiming to avoid congestion by limiting the data backlog of circuits. Secondarily, we want to achieve max-min fairness of the network. To those ends, we first present an optimization-based method to obtain max-min fairness of an overlay network (Theorem 1) in Subsection 3.1, which we have previously derived in [16]. However, the presented Theorem 1 cannot directly be used for congestion control, as it would require global knowledge and control authority of the Tor network. Instead, it serves as the basis for our proposed distributed MPC formulation, for which we establish the preliminaries in Subsection 3.2. We introduce the states, inputs, and system dynamics as well as the concept of information exchange between adjacent nodes. In comparison with our previous work [16], this concept has been extended to address several shortcomings in previously unconsidered situations. Most importantly, PredicTor nodes are now capable of requesting an exact rate increase from their successor nodes. The full optimal control problem is stated in Subsection 3.3. We discuss the interaction of PredicTor and a Tor relay in Subsection 3.4.

3.1 Optimization-Based Fairness

We present an optimization-based method (Theorem 1) to achieve max-min fairness. For this, we first introduce the formal notion of a bottleneck.

Definition 4. For a circuit $i \in P_\alpha$ and a rate vector $r$, we denote node $\alpha \in N$ a bottleneck, if

$$\sum_{i \in P_\alpha} r_i = C_\alpha, \quad \forall j \in P_\alpha : r_i \geq r_j.$$  \hfill (7)

Lemma 1. Let $r^f$ be a max-min fair rate vector. Each circuit $i \in P$ has exactly one bottleneck. This bottleneck is the global rate-limiting factor of the circuit under stationary conditions.

Proof. The proof is shown in [7]. \hfill $\Box$

This allows us to state the following theorem, which we previously introduced in [16].

Theorem 1. An overlay network achieves max-min fairness with rate $r = r^{max} - \Delta r$ as the optimal solution of

$$c = \min_{\Delta r} \sum_{i \in P} \Delta r_i^2$$

subject to:

$$r^{max} - \Delta r \in R_f,$$

$$0 \leq \Delta r \leq r^{max},$$

where $\Delta r$ is an auxiliary variable that can be interpreted as the unused rate with respect to the arbitrary upper limit $r^{max}$, which must satisfy $r^{max} \geq \max(C_1, C_2, \ldots, C_n)$.

Proof. The proof is presented in [16]. \hfill $\Box$
Fig. 2. Information exchange (predicted future trajectories in bold font) of node $\alpha$ with adjacent nodes. From the perspective of $\alpha$, all predecessor nodes are summarized as $\beta$ and all successor nodes as $\gamma$ for the sake of a concise notation. The rates at which data is sent at time $k$ for circuit $i$ at node $\alpha$ is $r_{\text{out},\alpha,i}^k$.

Theorem 1 allows us to obtain the global *max-min fair* rate $r$ of an overlay network as the solution of a convex optimization problem. Intuitively, the formulation in Theorem 1 works because we are minimizing the rate that is not allocated with respect to some arbitrary upper limit and under consideration of feasible rates. The quadratic term results in fairness because it is always desirable to allocate a higher rate (i.e., reduce $\Delta r$) to the circuit with the smallest rate (i.e., with the highest $\Delta r$).

### 3.2 Distributed MPC

In this subsection, we present the preliminaries for the statement of the PredicTor optimal control problem. We define states, inputs, and the dynamic system equation and introduce our concept for distributed MPC. This includes the question of which information is exchanged and how it is incorporated into the optimal control problem to achieve our previously defined control goals. For the interaction of multiple nodes, we denote $\alpha \in N$ the currently considered node, with connections to predecessor ($\beta$) and successor ($\gamma$) nodes. For the current node $\alpha$, it is irrelevant whether the incoming data comes from several nodes or from only a single node. To simplify the notation, we assume that all incoming data (even for different circuits) come from a single predecessor node $\beta$ and are forwarded to a single successor node $\gamma$. The interaction of multiple controllers is illustrated in Figure 2 and will be discussed in the following.

The controller at node $\alpha$ takes local decisions regarding incoming and outgoing rates under consideration of predicted future actions from the adjacent nodes. Predictions are obtained on the basis of dynamic models in the form of Equation (5). We first introduce the state $s_{\alpha}^k$, which denotes the queue size for all circuits $i \in P_\alpha$ in node $\alpha$ and at timestep $k$. The dynamic model equation can be written as

$$s_{\alpha}^{k+1} = s_{\alpha}^k + \Delta t \left( r_{\text{in},\alpha}^k - r_{\text{out},\alpha}^k \right),$$

where $\Delta t$ denotes the sampling time. As inputs in Equation (9), we introduce the incoming $r_{\text{in},\alpha}$ and outgoing $r_{\text{out},\alpha}$ rate. For the optimal control problem, we first introduce trivial constraints for the queue size

$$0 \leq s_{\alpha}^k \leq s_{\alpha}^{\max},$$

where $s_{\alpha}^{\max}$ represents the maximum queue size allowed for node $\alpha$. The constraints ensure that the queue size remains within a bounded range, preventing overflow or underflow scenarios.
for the rates
\begin{align}
0 & \leq r_{\text{in},\alpha}^k \\
0 & \leq r_{\text{out},\alpha}^k,
\end{align}
and for the link capacities
\begin{align}
\sum_{i \in P_{\alpha}} r_{\text{in},\alpha,i}^k & \leq C_{\alpha}^{\text{in}} \\
\sum_{i \in P_{\alpha}} r_{\text{out},\alpha,i}^k & \leq C_{\alpha}^{\text{out}}.
\end{align}

We have additional constraints regarding the incoming and outgoing rates, which depend on the actions of the adjacent nodes. From the successor node $\gamma$, we receive information about $r_{\text{in},\gamma}^k$, which limits the local outgoing rate as follows:
\begin{align}
r_{\text{out},\alpha}^k & \leq r_{\text{max},\alpha}^{k-1} = r_{\text{in},\gamma}^k.
\end{align}

Note that we consider $r_{\text{in},\gamma}^{k-1}$ (the successor’s information from the previous timestep $k-1$) since the information is delayed. The constraints for the incoming rate $r_{\text{in},\alpha}^k$ are considerably more complex. From the source node, we receive the predicted outgoing rate $r_{\text{out},\beta}^k$, the predicted circuit queue $s_{\beta}^k$ and a virtual outgoing rate $\hat{r}_{\text{out},\alpha}^k$. With this information, we constrain $r_{\text{in},\alpha}^k$ in two ways. First, we introduce an additional variable $\tilde{s}_{\alpha|\beta}^k$, which denotes the estimated queue size of node $\beta$ from the perspective of node $\alpha$ at time $k$. To express $\tilde{s}_{\alpha|\beta}^k$, we introduce the state variable $\Delta s_{\alpha|\beta}$, such that
\begin{align}
\tilde{s}_{\alpha|\beta}^k & = s_{\beta}^k - \Delta s_{\alpha|\beta},
\end{align}
with the dynamic system equation in the form of Equation (5):
\begin{align}
\Delta s_{\alpha|\beta}^{k+1} & = \Delta s_{\alpha|\beta}^k + \Delta t (r_{\text{in},\alpha}^k - \hat{r}_{\text{out},\alpha}^k).
\end{align}

Note that in contrast to Equation (13), we consider information from the source node $\beta$ at the current timestep $k$, as both the control action and the information are delayed. Equation (14) states that any value $r_{\text{in},\alpha}^k \neq r_{\text{out},\beta}^k$ will adjust the predicted circuit queue at the predecessor node. This way, we can indirectly constrain the incoming rate by enforcing
\begin{align}
\tilde{s}_{\alpha|\beta}^k & \geq 0,
\end{align}
which ensures that the incoming rate can only be increased as long as data are available in the source node.

A problem arises if the availability of data is not the rate-limiting factor at the source node. To cope with this situation, we propose a new mechanism for the source node to request a rate increase, which is incorporated as the second constraint on $r_{\text{in},\alpha}^k$. For this mechanism, we introduce an additional state $\hat{s}_{\alpha}^k$ and input $\hat{r}_{\text{out},\alpha}^k$ with the dynamic model equation
\begin{align}
\hat{s}_{\alpha}^{k+1} & = \hat{s}_{\alpha,i}^k + \Delta t \left( r_{\text{in},\alpha}^k - \hat{r}_{\text{out},\alpha}^k \right).
\end{align}

State, input, and dynamics are reminiscent of Equation (9), with the difference being that $\hat{s}_{\alpha}^k$ denotes the virtual queue size and $\hat{r}_{\text{out},\alpha}^k$ the virtual outgoing rate. These variables are virtual in the sense...
that they do not respect the rate constraint imposed by the successor node in Equation (13); rather they respect only the local constraints
\[ 0 \leq \hat{r}_{out,\alpha}^k, \]  
(17)

\[ \sum_{i \in P_\alpha} \hat{r}_{out,\alpha}^k \leq C_{out}^\alpha, \]  
(18)

and
\[ 0 \leq s^k_{\alpha} \leq s^{\text{max}}_{\alpha}. \]  
(19)

In this regard, the virtual outgoing rate \( \hat{r}_{out,\alpha, i}^k \) can be interpreted as the potential of node \( \alpha \) to increase the rate for circuit \( i \). Node \( \alpha \) receives the respective information from source node \( \beta \) as \( \hat{r}_{out,\beta}^k \). The most straightforward way to consider this information at node \( \alpha \) is to enforce
\[ r_{in,\alpha}^k \leq r_{in,\alpha}^{\text{max},k} = \hat{r}_{out,\beta}^k, \]  
(20)

which complements Equation (13) for the incoming rates. In practice, however, we found that with \( r_{in,\alpha}^{\text{max},k} = \hat{r}_{out,\beta}^k \), the incoming rate should be limited with
\[ 0 \leq \sum_{l=0}^{k} \left[ r_{in,\alpha}^{\text{max},l} - r_{in,\alpha}^l \right]. \]  
(21)

In most cases, the effect of the constraint in Equation (21) is similar to the constraint in Equation (20). The difference is that Equation (20) enforces a concrete upper limit for the incoming rate at time \( k \), whereas Equation (21) balances the limit over the horizon. This is beneficial as the sequence \( \hat{r}_{out,\beta}^k \) often contains single elements with very high data rates that cannot necessarily be fully utilized by the successor at that exact point in time.

### 3.3 Optimization Problem

In the following, we propose an optimal control problem for congestion control with fairness formulation for node \( \alpha \), predecessor node \( \beta \), and successor node \( \gamma \). As optimization variables, we introduce the states \( s_{\alpha}, \Delta s_{\alpha|\beta}, \) and \( \hat{s}_{\alpha} \) with their respective dynamics in Equations (9), (14b), and (16). Furthermore, we optimize the inputs \( \Delta r_{in,\alpha} \) and \( \Delta r_{out,\alpha} \) from which rates are determined with
\[ r_{in,\alpha} = r_{in,\alpha}^{\text{max}} - \Delta r_{in,\alpha}, \]  
(22)

\[ r_{out,\alpha} = r_{out,\alpha}^{\text{max}} - \Delta r_{in,\alpha}. \]  
(23)

To express the newly introduced variable \( \hat{r}_{out,\alpha} \), we introduce two optimization variables \( \Delta r_{out,\text{extra}} \) and \( r_{out,\text{minus}} \), such that
\[ \hat{r}_{out,\alpha} = r_{out,\alpha} + \left( r_{out,\alpha}^{\text{max}} - \Delta r_{out,\text{extra}} \right) - r_{out,\text{minus}}. \]  
(24)

Thus, the virtual outgoing rate \( \hat{r}_{out,\alpha} \) is not chosen independently but rather as a deviation from the outgoing rate \( r_{out,\alpha} \). This mathematical construction was found to aid the convergence to the global max-min fair solution.
Considering Equations (22), (23), and (24), we state the OCP as follows:

\[
\begin{align*}
\min_{s_{\alpha}, \Delta s_{\alpha|i}, \hat{s}_{\alpha}, \Delta r_{\text{in}, \alpha}, \Delta r_{\text{out}, \alpha}, \Delta r_{\text{out, extra}}, \hat{r}_{\text{out, minus}}} & \sum_{k=0}^{N_{\text{horz}}} d_k \left( (\Delta r_{\text{in}, \alpha}^k)^2 + (\Delta r_{\text{out,extra}}^k)^2 + (\Delta r_{\text{out, minus}}^k)^2 \right) \\
\text{subject to} & \\
\text{queue dynamics in Equations (9), (14b), (16):} & \quad s_{\alpha}^{k+1} = s_{\alpha}^k + \Delta t \left( r_{\text{in}, \alpha}^k - r_{\text{out}, \alpha}^k \right), \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad \Delta s_{\alpha|i|^\beta} = \Delta s_{\alpha|i|^\beta} + \Delta t \left( r_{\text{in}, \alpha}^k - r_{\text{out}, \beta}^k \right), \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad \hat{s}_{\alpha}^{k+1} = \hat{s}_{\alpha}^k + \Delta t \left( r_{\text{in}, \alpha}^k - \hat{r}_{\text{out}, \alpha}^k \right), \quad \forall k = 0, \ldots, N_{\text{horz}} \\
\text{queue constraints in Equations (10), (15), (19):} & \quad 0 \leq s_{\alpha}^k \leq s_{\alpha}^{\max} \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad 0 \leq s_{\alpha|i|\beta}^k \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad 0 \leq \hat{s}_{\alpha}^k \leq \hat{s}_{\alpha}^{\max} \quad \forall k = 0, \ldots, N_{\text{horz}} \\
\text{rate in constraints in Equations (11a), (12a), (21):} & \quad 0 \leq r_{\text{in}, \alpha}^k \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad \sum_{i \in P_{\alpha}} r_{\text{in}, \alpha,i}^k \leq C_{\alpha}^{\text{in}} \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad 0 \leq \sum_{i=0}^{k} \left[ r_{\text{in}, \alpha}^{\max, l} - r_{\text{in}, \alpha}^l \right] \quad \forall k = 0, \ldots, N_{\text{horz}} \\
\text{rate out constraints in Equations (11b), (13), (12b):} & \quad 0 \leq r_{\text{out, extra}}^k \leq r_{\text{out, extra}}^{\max,k} \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad \sum_{i \in P_{\alpha}} r_{\text{out, extra},i}^k \leq C_{\alpha}^{\text{out}} \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad 0 \leq \hat{r}_{\text{out, extra}}^k \quad \forall k = 0, \ldots, N_{\text{horz}} \\
\text{virt. rate out constraints in Equations (18), (17):} & \quad \sum_{i \in P_{\alpha}} \hat{r}_{\text{out, extra},i}^k \leq C_{\alpha}^{\text{out}} \quad \forall k = 0, \ldots, N_{\text{horz}} \\
& \quad 0 \leq \hat{r}_{\text{out, extra}}^k \quad \forall k = 0, \ldots, N_{\text{horz}} \\
\text{initial conditions:} & \quad s_{\alpha}^0 = s_{\alpha}^{\text{init}}, \quad \Delta s_{\alpha|i}^0 = 0, \quad \hat{s}_{\alpha} = \hat{s}_{\alpha}^{\text{init}}. \quad (25n)
\end{align*}
\]

The optimization problem in Equation (25) is solved at each timestep and in each node of the network under consideration of the predicted trajectories of adjacent nodes \( r_{\text{in}, \alpha}^{k-1}, r_{\text{out, extra}}^k, \hat{r}_{\text{out, extra}}^k \) as well as the current size of the circuit queue in the current node \( s_{\alpha}^{\text{init}} \). Note that according to Equation (13), we set \( r_{\text{out, extra}}^{\max,k} = r_{\text{in}, \alpha}^{k-1} \) and, according to Equation (20), we have that \( r_{\text{in}, \alpha}^{\max} = \hat{r}_{\text{out, extra}}^k \).

The objective in Equation (25) is motivated by the presented Theorem 1 but with some important adaptations. Most notably, we introduced \( \Delta r \) variables for both the incoming and outgoing rates.
Introducing the control variable $\Delta r_{\text{in},a}$ allows one to control the incoming rate. This is of significant importance for the desired congestion control as it realizes that backpressure and data will be stopped from entering the network if it cannot be forwarded. The quadratic term in $\Delta r_{\text{out},a}$ ensures that the circuit queue is emptied even if there are no new packets entering the node.

Moreover, to further avoid congestion, PredicTor is explicitly designed to limit the circuit queues through the constraint in Equation (25d).

The objective in Equation (25) is further modified by introducing a discount factor $d$. This is necessary because na"ively implementing our presented fairness formulation also results in fairness along the prediction horizon, where it is always preferable to increase the rate of the smallest element in a sequence for a given circuit. In practice, however, we want to send and receive as soon as possible as long as instantaneous fairness is achieved. In the appendix of [16], we present a guideline on how to choose $d$ to obtain the desired behavior.

Note that the theoretical analysis of the feasibility and stability of the proposed MPC controller in Equation (25) is out of the scope of this work. However, we found that the proposed controller is stable and feasible for all investigated simulation studies.

### 3.4 Controller Integration

The proposed controller is implemented on the application layer of each node in the Tor network. At each time step, the problem in Equation (25) is solved with the most recent measurement of the circuit queue $s_{a}^{\text{init}}$ of the current node $a \in N$ and with the received information from adjacent nodes. The optimal solution for Equation (25) is converted to trajectories of incoming ($r_{\text{in},a}$) and outgoing ($r_{\text{out},a}$) rates, where the first element of $r_{\text{out},a}$ is used to control at which rate data are sent. In particular, we employ a token-bucket method [7] to shape the outgoing traffic. Note that we are controlling the data rates on a per-circuit basis, which is similar to how PCTCP [2] changes Tor’s circuit handling.

In order to exchange the trajectories between relays, we extend the Tor protocol with respective control messages. This is technically possible due to the extensibility of the Tor protocol, which allows the definition of new cell types. For the edges of each circuit that do not have a predecessor or successor to exchange data, we provide reasonable synthetic trajectories to bootstrap the data transfer and behave accordingly. For example, the first node in a circuit reads data from its source according to its computed incoming rate. While PredicTor is generally agnostic to the underlying transport protocol, we implement it using TCP as a reliability mechanism to avoid packet loss and packet reordering.

### 4 SECURITY AND PRIVACY CONSIDERATIONS

Extending a widespread anonymity network such as Tor in a fundamental way as PredicTor does requires great care to avoid reducing the security level and putting the users’ privacy in danger. While this section does not constitute a formal, complete security analysis, it aims to give an intuition of how PredicTor would interfere with the existing security guarantees and privacy level in Tor. In order to do so, we first recall Tor’s adversary model and then review typical attacks on Tor, analyzing how PredicTor relates to them. For this, we make use of the categorization of Tor attacks presented in [3]. Still, PredicTor was primarily designed for exploring new directions towards multi-hop congestion control and does not claim to fully satisfy the security requirements needed for production use.

*Adversary Model.* The Tor network aims to protect the privacy of its users. It obfuscates their IP addresses by relaying traffic over circuits of intermediate hops. In this setting, Tor assumes the
following adversary [13]. An attacker may control a certain fraction of the network, including underlay links and relays. However, Tor does not protect against a global adversary that can monitor the whole network. Consequently, Tor aims to protect against local adversaries but cannot currently avoid end-to-end traffic confirmation attacks.

One design aspect that goes hand-in-hand with this assumption is that Tor does not rely on any specific trust relationship between relays. In particular, the Tor protocol tries to make it as hard as possible for cooperating malicious relays to de-anonymize users. One essential building block for this is the use of telescope-like onion encryption such that each a relay within a circuit can see only its immediate predecessor and successor. Payload data, including the target address, is visible end-to-end between the client and the exit only. All other information for building and maintaining circuits is visible hop-by-hop only so that the insight every single relay can gain about the overall circuit is minimized. The design of PredicTor’s network protocol is in line with this general concept: feedback data is exchanged between adjacent relays only, utilizing Tor’s existing cryptography and trust assumptions.

Information Leakage from Feedback Messages. Although feedback messages themselves are exchanged only between directly neighboring relays, one can argue that parts of the information they contain actually trickle over more than one hop. This is because feedback information is taken into account by the optimizer and, therefore, implicitly influences the feedback information that is, in turn, sent to other relays after the optimization step. We cannot see how such information could be exploited by malicious relays but cannot prove this kind of information leakage irrelevant, either. This would require a more in-depth analysis, which is subject to future work.

Our initial assessment, however, can be summarized as follows. The potential danger would be that local relays could learn more about the overall circuit than before, e.g., inferring parts of the circuit topology. For such inference, obtaining the exact number of circuits handled by another relay may be useful to the adversary. Feedback messages in PredicTor contain per-circuit trajectories but only for the circuits that are multiplexed between any two adjacent relays. The same piece of information is already available to vanilla Tor relays for circuit handling. Obtaining the overall number of circuits handled by another relay would, just as before, require heuristics that make use of additional information, such as the data rate advertised in the network consensus. Therefore, we do not think that PredicTor would facilitate such inference. The same is true for the exchanged data rates. Since these are propagated between relays after optimization, malicious relays could try to infer characteristics of relays at the far end of the circuit, for example, ruling out relay candidates that would lead to different bottleneck values. However, such inference could also be carried out as of today simply by locally measuring the throughput achieved per circuit.

Traffic Confirmation Attacks. The most fundamental vulnerability of Tor is its susceptibility to timing-based traffic confirmation attacks that could either be carried out by a global adversary or by an adversary that controls both the entry and the exit relay. In general, low-latency anonymity networks cannot prevent traffic confirmation attacks. However, even if such attacks cannot be prevented entirely, their difficulty depends largely on the temporal correlation between data entering and leaving the network. Consequently, better and more predictable performance, as is achieved by PredicTor, may facilitate traffic confirmation attacks. This is an inherent challenge every performance enhancement for Tor has to face. On the other hand, better performance bears the potential to attract a broader user base, strengthening the anonymity set. Thus, it is not entirely clear whether the overall privacy level would be harmed. The precise interdependencies between these factors are one of our main future research directions.
Routing and Circuit Selection. Adversaries may be able to increase their chances of successfully attacking a larger portion of the user base by taking into account the circuit selection process that is carried out by the Tor clients. Likewise, if adversaries not only control individual relays but also control Autonomous Systems (AS), this can be problematic. PredicTor, however, is fully orthogonal and does not touch circuit selection or routing. Therefore, it does not increase vulnerability to these attacks.

Website Fingerprinting and Watermarking. One attack vector has been researched extensively in past works by inferring communication contents by analyzing the timing of the encrypted data traffic. Closely related, there are watermarking techniques that actively insert traffic pattern peculiarities in order to make flows more easily recognizable. We argue that both attack strategies are either not touched by PredicTor or even become more difficult because the explicit traffic handling defined by PredicTor results in smoother and more homogeneous traffic patterns on the wire, as we will show in Section 5.2.

Congestion Attacks and Denial of Service (DoS). Attackers can try to divert target traffic from relays they do not control to their own relays by artificially congesting parts of the network up to the point where benign relays cannot continue operation, referred to as denial of service (DoS). As far as traffic congestion is concerned, PredicTor is likely more resilient to such attacks than vanilla Tor because it handles situations of congestion or load much more explicitly. Attackers cannot as easily flood the network, because the controllers running at each relay optimize the traffic flows to keep queues low. On the other hand, we suspect PredicTor to be prone to DoS attacks that specifically target the optimizer. Although the underlying optimization problem can be solved efficiently, the computational effort still depends on the number of circuits involved. Therefore, an attacker could trigger increased resource usage by constructing tailored circuits that increase the difficulty of PredicTor’s optimization problem.

All in all, our initial security and privacy assessment shows that future work would be necessary to ensure that PredicTor does not introduce new attack vectors. On the other hand, it can also help in mitigating several existing attacks.

5 EVALUATION AND DISCUSSION

Evaluating PredicTor on the live Tor network is prohibitive due to the potential of risking users’ anonymity. Instead, we here investigate its behavior by carrying out simulation studies.

It should be noted that, in its current form, PredicTor is not meant for immediate real-world application on the Tor network. Instead, it constitutes a concept study opening novel research direction towards realizing congestion control in complex networks. Therefore, all of our experimentation has the goal of maximizing the understanding of this new approach, applying distributed model predictive control for congestion control. We aim to clearly point out benefits and potential drawbacks of such strategies. In particular, our evaluation covers the PredicTor controller’s detailed behavior and its implications. We look at the isolated behavior of single controllers as well as the overall system behavior that emerges from the cooperative interaction of multiple controllers. To put the results into context, we compare PredicTor to vanilla Tor as well as PCTCP [2], an alternative circuit handling strategy for Tor. From these observations, we deduce insight about the benefits, inherent limitations, and the expected applicability of such approaches.

Our evaluation strategy is twofold: First, we analyze PredicTor’s behavior in small toy scenarios that allow us to better understand its behavior in situations that are simple enough to be investigated by hand. By doing so, we establish an intuition of its behavior. To this end, we first investigate the working of a single, isolated PredicTor controller before setting up multiple controllers to
cooperate. This way, we can analyze the behavior of a single, isolated PredicTor controller as well as the interaction between multiple controllers.

We take our evaluation further by scaling up our experiments to more complex networks. This serves as a means of exploring the applicability of PredicTor in more realistic scenarios. On the one hand, we thus verify whether PredicTor’s claimed benefits do also exist in scenarios that are not as easy to understand as the toy scenarios before. On the other hand, we investigate to what extent the underlying assumptions made in PredicTor collide with reality and what implications this has for further research in the field. Lastly, we evaluate how PredicTor handles different traffic patterns (bulk and web traffic).

Implementation. As laid out before, PredicTor comprises, on the one hand, the controller logic that uses MPC to find the optimal data rates based on the implemented system model and optimization objectives. On the other hand, these control decisions have to be realized in the network and the predicted trajectories have to be exchanged with other relays. The structure of our prototype implementation of PredicTor also exhibits these two main tasks. We implement the PredicTor core model in Python, utilizing CasADi [5] in combination with IPOPT [44] and the MA27 [3] linear solver for fast state-of-the-art optimization. For implementing the network behavior, we embed it into nstor [40], an implementation of Tor for the ns-3 network simulator. Our implementation thus covers PredicTor, vanilla Tor, and PCTCP. PCTCP differs from vanilla Tor in that it establishes a separate connection per circuit instead of multiplexing them. While the overall network simulation is carried out by nstor, each simulated relay has access to the controller code library for carrying out its local optimizations. The results are then used as the Tor relay’s scheduling strategy in the network simulation, This means throttling data transmission based on the controller’s optimization output and exchanging the predicted trajectories between relays. Our implementation is publicly available online.

The results presented in the following are obtained with a discount factor of $d = \frac{1}{3}$, as discussed in the appendix of [16]. For the prediction horizon, we choose $N_{\text{horz}} = 10$.

Metrics. In order to assess PredicTor’s performance, we quantify different parameters that are relevant for comparing it to existing approaches. For each of these parameters, we initially evaluate the steady state behavior. First, we consider the latency of the data transfer. Apart from the physical underlay latency, which denotes a natural lower bound, latency stems primarily from the existence of buffers and queues in the network. Since the reduction of queue sizes is an explicit optimization goal of PredicTor, we expect a considerable enhancement in this regard. We define our notion of latency as follows. For each data transfer through the network (running over a circuit of multiple relays), we define latency as the difference in time between when it reaches its destination and when it entered the (overlay) network. Therefore, we focus explicitly on the Tor network itself and disregard additional latency that may occur, for example, for the communication between the exit relay and an outside web server. This approach ensures that we capture the two important consequences of latency: first, the impact on the user who experiences additional waiting time before seeing the response to a request and second, large queue sizes also mean a higher load on the network itself. Therefore, small queues—and, thus, lower latency—are desirable also from a network perspective in reducing congestion. We refer to the total amount of data present in the network at any point in time as backlog. For latency, we employ a byte-wise perspective. That is,
we precisely track for each payload byte the times of sending and receiving and aggregate them into an overall value by taking the average.

Another relevant metric is the throughput that is achieved by each of the circuits. On the one hand, it expresses how well the network is utilized. On the other hand, we can use these characteristics to define a notion of fairness in the network. As explained before, PredicTor aims at establishing max-min fairness for all circuits, which Tor is not currently capable of. Given a specific topology of circuits and relays, we calculate the optimal max-min fair data rate distribution for this scenario. We can then compare the observed values from our simulations to this optimum in two ways. For an in-depth analysis of the resulting data rate distributions, we visualize them as cumulative distribution functions in a CDF plot. However, if we only want a single value to express the degree of fairness, we make use of the following construction. Let \( r_{f}^{1}, \ldots, r_{f}^{n} \) be the max-min fair data rate distribution and let \( r_{1}, \ldots, r_{n} \) be the observed data rates. We then define the fairness index \( F \) as follows:

\[
F = 1 - \frac{\sum_{i=1}^{n} |r_{f}^{i} - r_{i}|}{\sum_{i=1}^{n} r_{f}^{i}}
\]

Put differently, \( F \) denotes the share of traffic that behaves according to max-min fairness. While other established fairness measures exist — most notably, Jain’s fairness index \([21]\) — they are not applicable here. Jain defines fairness as a uniform allocation of a resource. Since we make use of max-min fairness, however, a uniform data rate distribution is not necessarily the optimal choice.

**Limitations.** One of our main simplifications includes that we do not simulate the transmission of feedback messages over the wire; rather, we emulate their exchange “out of band.” Since feedback traffic is independent of the network speed, running the simulations at different simulated data rates, one could achieve arbitrary goodput-overhead ratios, which we refrain from doing. Our intention is to evaluate the scheduling behavior itself as a baseline instead of capturing artifacts that stem purely from implementation details such as packet format. However, we note (and later discuss) that, in real networks, feedback overhead would constitute a severe issue due to its linear growth with the number of circuits. For this prototype, we base the data transfer on TCP (like Tor and PCTCP) instead of introducing a tailored transport protocol. Thus, PredicTor merely takes the role of a scheduler. We will later discuss that this approach can still be beneficial for robustness.

**5.1 Single Controller**

We first present an investigation of the decision-making process of PredicTor’s proposed controller from Equation (25) for a single node. In order to highlight several interesting aspects of its behavior, we investigate an open-loop prediction. This means that we solve the optimal control problem in Equation (25) once and display the resulting predicted future trajectories. In the closed-loop control application, these predictions will change repeatedly as new information becomes available.

For the investigation, we consider the small-scale topology presented in Figure 1. The topology consists of six relays handling a total of three circuits. All three circuits meet in a shared bottleneck. Two of these circuits originate from the same sending relay. Therefore, the scenario demonstrates a simple congestion situation. We focus on the controller at the bottleneck and denote \( \alpha \) the current node, \( \beta \) its predecessors, and \( \gamma \) its successors.

We investigate a synthetic scenario with manually defined trajectories from the adjacent nodes. In particular, we define for the predecessor node \( r_{\text{out,}^\beta}, r_{\text{out,}^\beta}, s_{\beta}^{k} \). For the successor node, we define \( r_{\text{in,}^\gamma}^{k-1} \). We set \( r_{\text{out,}^\alpha}^{\text{max,}k}, r_{\text{in,}^\gamma}^{k-1}, r_{\text{in,}^\alpha}^{\text{max,}k}, r_{\text{out,}^\beta}^{k} \). Additionally, the initial buffer size \( s_{\alpha}^{\text{init,}k} \)
is required. Based on this information, the solution for Equation (25) allows computation of the trajectories $r_{\text{in},\alpha}$, $r_{\text{out},\alpha}$, $s_{\alpha,i}$, $s_{\alpha}$, and $\tilde{s}_{k\alpha|\beta}$. The trajectories are displayed in Figure 3 and will be discussed in the following.

The most important decision of the PredicTor controller is with respect to the outgoing rates $r_{\text{out},\alpha}$. The first element of this sequence determines the rate at which data are sent until the next sampling instance. In Figure 3, we can see at 1 that all circuits obtain the same rate at the beginning of the sequence. At this point in time, the rate is only limited by the node capacity $c_{\alpha}^{\text{out}}$, which can be seen in 2. Over the course of the prediction horizon, the outgoing rate for circuit 2 is increasing, whereas the rates for circuits 1 and 3 are decreasing. This behavior is due to the buffer sizes for the circuits, shown in 3. Here, we can see that even with an increasing rate, the buffer for circuit 2 is growing whereas the buffers for circuits 1 and 3 are approaching zero. With the buffer size for circuits 1 and 3 close to zero, the outgoing rate for these circuits approaches the incoming rates $r_{\text{in},\alpha}$, shown in 4, at the end of the horizon. Under stationary conditions, the incoming rates $r_{\text{in},\alpha}$ are typically equivalent to the predicted outgoing rates $r_{\text{out},\beta}$ of the source node $\beta$, which can also be seen in 4 for circuit 3. For circuit 1, however, the algorithm determines to increase $r_{\text{in},\alpha,1}$ with respect to $r_{\text{out},\beta,1}$. This can be seen in 5. When increasing the incoming rate, PredicTor needs to consider $r_{\text{max}}$ and the respective constraint in Equation (21). Note that this constraint is not enforced at each timestep with $r_{\text{in},\alpha} \leq r_{\text{max}}^{\text{in},\alpha}$ but the limit increases at each timestep with $r_{\text{max}}^{\text{in},\alpha} \geq 0$. This can also be seen for circuit 1 in 5.

Since the algorithm determines to increase the incoming rate $r_{\text{in},\alpha,1}$ with respect to the prediction of the source node $r_{\text{out},\beta,1}$, it also predicts a deviation in the buffer size at the source node. In
Fig. 4. Data rates of the circuits in the sample topology (scenario 1) over time.

We can see that originally the buffer size $s_{\beta, 1}$ for circuit 1 is predicted to be constant over the horizon. The obtained trajectory $\tilde{s}_{\alpha|\beta, 1}$ takes into consideration the increased $r_{\text{in}, \alpha, 1}$ and predicts that the buffer for circuit 1 at node $\beta$ will be emptied at timestep $k = 5$. Consequently, we can see at $k = 5$ that the rate $r_{k+5}$ is zero.

A final aspect to mention is $\hat{r}_{\text{out}, \alpha}$. This virtual outgoing rate is different from $r_{\text{out}, \alpha}$ as it does not consider the constraint $r_{\text{out}, \alpha, 1} \leq r^{\text{max}}_{\text{out}, \alpha}$. This can be seen in for circuit 2. The purpose of this virtual rate is to request from the successor node an increase in $r^{\text{max}}_{\text{out}, \alpha}$ such that at a later iteration the true rate can be increased.

In summary, we find that the solution to the PredicTor problem (see Equation (25)) leads to sound and interpretable behavior in terms of its predicted future trajectories. For the synthetic scenario, it can be seen that the controller attempts to achieve fairness and to avoid congestion while utilizing the available resources of the network. The results allow no conclusions regarding performance, however, as only a single controller in an open-loop solution is investigated.

### 5.2 Interaction of Multiple Controllers

We next carried out a full simulation of the sample network. This now includes not only the isolated controllers but also the interaction between them as well as the application logic and network stack behavior. To this end, ns-3 allows us to achieve a high degree of realism by emulating the network down to the physical layer, including queuing effects, packet loss, and so on. We refer to this kind of simulation as **closed-loop**, because each MPC step takes into account the current state of the system, determined from measurements and information exchange between relays. For this simple setup, we define all underlay links to have the same, constant latency. We will lift this assumption in later experiments. We compare the performance of PredicTor to vanilla Tor and PCTCP.

We investigate two scenarios that differ slightly by circuit behavior. The three circuits start at slightly different times, purely for easier visualization. In scenario 1, circuits 1 and 3 have an infinite source of packets to forward, whereas circuit 2 stops and restarts twice during the simulation. This allows us to better investigate how PredicTor assigns data rates to each of the circuits. In scenario 2, all circuits have an infinite source of packets. We use this setup for comparing the absolute values of achieved data rates more easily.

Figure 4 shows the data rates of the individual circuits in scenario 1 over the course of the simulation time. These per-circuit values were measured in ns-3 by recording the outgoing rates at the bottleneck. We can see that PredicTor exhibits a desirable behavior with constant, sustainable rates and smooth transitions when circuit 2 stops and restarts. Fair behavior can be observed in these transitions: All circuits share the same rate during activity and circuits 1 and 3 are allocated the same, higher rate when circuit 2 stops sending. The sum of all rates is visibly constant over
time. On the other hand, vanilla Tor and PCTCP show erratic, oscillatory behavior where bursts are followed by very low rates, while the individual circuits take turns sending data. Fairness cannot be assessed visually for Tor and PCTCP, which is why we quantify it later.

We further compare PredicTor, Tor, and PCTCP in Figures 5 and 6, in which we display the backlog and latency. PredicTor succeeds at its primary goal of sustaining a manageable backlog, especially compared with vanilla Tor and PCTCP. The importance of this effective congestion control becomes apparent in Figure 6, in which we compare histograms for the latencies of received packets. With an average latency of 93 ms, PredicTor significantly improves on vanilla Tor (553 ms) and PCTCP (635 ms). Based on the underlay link latency, the theoretical minimum was at 80 ms.

To summarize our findings from this simple network topology, we present the achieved latency and data rate values per circuit in Table 1. As mentioned before, the data rates stem from a slightly different setup (scenario 2), in which circuit 2 does not stop sending. Otherwise, the data rates would not be easily comparable. Regarding throughput, the three methods perform very similarly,
the difference being that PredicTor achieves near perfect fairness \( F = 0.98 \). Vanilla Tor clearly discriminates circuits 1 and 2, which share a connection \( F = 0.68 \). PCTCP, as expected, manages to revise this effect to some extent in this simple setup \( F = 0.95 \).

We conclude that PredicTor bears the potential to provide a clear advantage with respect to latency and fairness. However, it should be noted that PredicTor also introduces significant complexity compared with the previous methods. On the other hand, the optimization problem in Equation (25) is convex, which guarantees a global solution in polynomial time. For the given scenario, obtaining a solution takes around 10 ms (laptop-grade CPU). The problem complexity (number of optimization variables and constraints) grows linearly with the number of circuits per node. Therefore, it is expected that larger topologies can also be tackled with this approach in real time. However, scaling the network excessively may well render the approach unusable at some point. This also becomes apparent when considering the overhead induced by the exchange of feedback messages.

5.3 Impact of Network Complexity

In the previous subsections, we have demonstrated the general utility of PredicTor for congestion control in the Tor network. While this constitutes an important precondition for applying such approaches, it is not sufficient for thoroughly assessing its potential. Therefore, we now go a step further and investigate the extent to which the observed benefits and drawbacks also apply to more realistic network situations. In order to do so, we now focus on more complex networks that are not trivial to comprehend in every simulated detail. In the course of this evaluation, we put a special focus on the assumptions and trade-offs made in PredicTor. Note that this evaluation is still explorative in nature.

We first analyze PredicTor’s behavior in networks that are significantly larger and more complex than in Section 5.2 but otherwise do not differ much from the simulation assumptions. In particular, the underlay links still have a uniform, constant latency.

We construct random networks of different sizes. We fix the number of relays at 50 but vary the number of circuits, ranging from 10 to 1,000. Each circuit consists of a random sequence of three relays. We chose this simple network model for several reasons. First, it allows us to easily realize different levels of congestion in the network. Since we want to compare PredicTor against existing congestion control mechanisms for the Tor network, it is desirable to investigate the influence of network load. Second, we do not want to make too strict assumptions on the precise topology. Instead, we regard a completely random network as a suitable baseline to compare against. Much more elaborate models of the Tor network do exist [22, 24]. In fact, our methodology is still influenced by [24], for example, in that we pay attention to generating a completely new random network for every single simulation run to avoid statistical bias.

Our focus is mainly on bulk traffic, that is, each circuit transfers an infinite stream of data. After a lead time, we evaluate the steady state (identified manually by ourselves), that is, the last two seconds of simulation time. For this time span, we again analyze the following metrics: byte-wise end-to-end latency, throughput, and fairness. For each data point, we carry out the simulation 25 times (with different random seeds) and report mean values. In Section 5.5, we lift the assumption of having only bulk traffic and consider a mix of bulk and interactive web traffic instead.

**Latency and Throughput.** We first focus on the latency and throughput that is achieved by each of the three algorithms with growing congestion in the network. Figure 7 presents our results. With respect to latency, we can see that PredicTor offers great potential to heavily improve on the status quo (see Figure 7(a)). In particular, by explicitly requiring small queues during optimization, PredicTor achieves low latency independently of the number of circuits. In contrast, latency...
grows indefinitely for denser networks in the case of vanilla Tor and PCTCP. This is because PredicTor does not “blindly” send data into the network; rather it does so only if the controller’s optimization result allows it based on local measurements and feedback from adjacent relays. The resulting lower backlog leads to much lower latencies, even for heavily crowded networks. In contrast, vanilla Tor and PCTCP have to rely solely on the state of their local TCP connections, which cannot take into account the state in the network more than one hop down the circuit. Therefore, they send too much data, leading to significant backlog and latency. The only way that vanilla Tor and PCTCP could react to congestion on the overall circuit would be Tor’s end-to-end window mechanism. However, this window has previously been identified to be too coarse-grained and rigid to help with efficient congestion control \cite{1}. In contrast to vanilla Tor, PCTCP can deal with extreme congestion slightly better due to its avoidance of head-of-line blocking in the case of packet loss, which becomes more relevant in these scenarios.

When looking at the achieved throughput, however, PredicTor cannot fully compete with the traditional approaches. Over the whole parameter range, it achieves considerably lower overall data rates, averaging at a disadvantage of around 20%. While this is an insight that was not apparent from the toy scenarios we examined in the previous section, we attribute it to two root causes. First, the controller behaves conservatively as far as data rate assignment is concerned. A circuit is given a share of the available bandwidth only after this was decided to be beneficial in the sense of the MPC optimization problem. This lack of aggressiveness differentiates PredicTor from the other approaches. Second, just as vanilla Tor and PCTCP, PredicTor currently uses TCP as the underlying transport protocol and acts as an additional scheduler on top of it. In the general case, it will therefore not be able to outperform approaches that only use TCP without an additional sending limit. Either way, we can state that the lower average throughput constitutes a clear trade-off that PredicTor makes in favor of lower latency.

Putting this relationship into perspective, one might argue that the lower latency is not an achievement of PredicTor itself but simply an artifact and a consequence of the lower throughput, because the lower data rates result in smaller queues. However, this is not the case, as another experiment shows. Out of the previously explored parameter space, we chose two scenarios that are representative for a low and high degree of congestion in the network, respectively (100 and 500 circuits, with 50 relays). For both of these scenarios, we introduced an artificial, application-layer throttling mechanism, reducing the amount of available bandwidth that each relay can use. We varied this throttling factor between 0.0 (no throttling at all) and 0.9 (only 10% of bandwidth remains) and recorded the achieved latency. The assumption was that artificially lowering the data

![Fig. 7. Performance in random networks with 50 relays and variable number of circuits. (a) Average byte-wise latency, and (b) average overall throughput (per-run sum of all circuits).](image-url)
Fig. 8. Impact of application-layer throttling on latency in networks with 50 relays. Note that reducing the data rate does not enable vanilla Tor and PCTCP to achieve latency values as low as PredicTor. Figure 8 reveals that the opposite is true for both the heavily and less congested networks. In fact, lowering the data rates mostly leads to an increase in latency with vanilla Tor and PCTCP. To understand this behavior, we have to emphasize that each data transfer through the Tor network does not consist of only one single TCP connection; rather, it denotes a multi-hop data transfer. Therefore, lowering the data rates does not automatically lead to a substantial reduction of backlog. Instead, the packets are queued at the application layer and experience the same throttling when being forwarded. We can thus conclude that the low latency is, in fact, an achievement of PredicTor and not only a side effect of the lower data rates.

Fairness. Another central promise of PredicTor is the achievement of much better fairness based on the notion of max-min fairness. We now evaluate the degree to which PredicTor can realize fairness in complex networks as well. Our results are based on the same simulation runs as for the latency and throughput evaluation.

In Figure 9(a), we show an individual simulation run with 750 concurrent circuits as a CDF plot of the data rates to visually inspect the fairness. We also included the max-min fair rate distribution as a baseline. As can be seen, vanilla Tor and PCTCP give most circuits either too low or too high data rates. In contrast, PredicTor very closely approximates max-min fairness. The only deviation that can be identified visually is that several circuits use less bandwidth than optimal max-min
would allow them to. This is in line with our previous observation that the traffic generated by PredicTor is rather conservative and the overall data rate tends to be lower than with the traditional approaches.

We validated and generalized the insight gained from the single simulation runs by calculating the fairness index $F$ for varying circuit numbers. The plot in Figure 9(b) reveals that PredicTor is highly effective at ensuring fairness, even in situations in which the network is heavily congested. The explicit max-min fairness formulation in PredicTor’s optimization goal consistently causes around 90% of the network traffic to adhere to max-min fairness. In contrast, vanilla Tor and PCTCP generally generate much less fair traffic. This becomes especially apparent the more congested the network is. Again, PCTCP performs slightly better than vanilla Tor but still cannot clearly surpass the threshold of around $F = 0.4$ if there is considerable congestion in the network. We can also see that, if there is only a little congestion, both of the traditional approaches generate fairer traffic. However, this is not because they can ensure this behavior in any kind. Instead, the lack of congestion also implies that more circuits can fully utilize the available bandwidth on their path. Therefore, a larger share of circuits can be regarded as behaving in a fair way.

5.4 Impact of Model Assumptions

As shown in the previous subsection, PredicTor is able to improve on both latency and fairness, even in complex, “crowded” networks. However, even if the concurrent data transmissions of many circuits in these simulations added a considerable degree of randomness to the network behavior, the scenario is still specific to the assumptions made in PredicTor’s system model. Most importantly, the underlay link latencies exactly match the values that are used for calculation in the model. In reality, this would not be the case, as many influences outside our model affect the connection. Such factors might include cross traffic on the Internet, routing topology changes, and others.

The system model describing the expected network behavior is crucial to the functioning of model predictive control approaches such as PredicTor. Thus, it is important to investigate to what degree the overall system is susceptible to deviations from the model. In this section, we focus on the robustness of PredicTor in the face of network behavior differing from PredicTor’s expectations drawn from its system model. We note that the strongest assumption made by PredicTor is that the latency of the underlay links can reliably be known in advance. Therefore, we now evaluate PredicTor’s behavior if this assumption is violated.

For this, we employ a similar setup as the one in Section 5.3. However, we now do not simulate uniform link latency. In contrast, we introduce a fuzziness factor $f$. The fuzziness $f$ defines the uncertainty in link latency as follows. If PredicTor’s system model expects a link latency of $l$, the link latency is instead chosen uniformly at random from the interval $[\max(l \cdot (1 - f), \epsilon); l \cdot (1 + f)]$. As a consequence of this construction, the larger the fuzziness value $f$, the larger will be the average deviation of the underlay link latencies from PredicTor’s system model. This gives us a concise parameter to evaluate the robustness of PredicTor against a system model mismatch. As a technical detail, we introduce a lower bound of some arbitrarily small value $\epsilon > 0$ for the latencies to avoid negative and zero-valued latencies. For fuzziness values $f > 1$, this by design shifts the distribution towards higher latencies.

We now fix the number of relays and circuits to evaluate PredicTor’s robustness by varying the link fuzziness. Since the analysis without link latency deviation has revealed that the performance differs depending on how crowded the network is, we carry out the following evaluation twice: first, with a circuit number of 100, representing a network situation with little congestion, and second, with 500 circuits, which induces much more congestion in the network. Again, each trial is repeated 25 times with newly generated network topologies.
We first consider the achieved latency, shown in Figure 10. Recall that in both cases (more and less congestion), PredicTor achieved much lower latency than vanilla Tor and PCTCP if the link latencies exactly matched the system model, as presented in Section 5.3. Introducing link fuzziness now creates a more differentiated picture. The first observation that can be made is that, for all of the considered Tor variants, the overall latency grows with a growing link fuzziness factor. This is not surprising due to the aforementioned shift of the latency distribution for large fuzziness values. A more significant observation, however, is that PredicTor is affected by an increasing fuzziness much more than the traditional approaches in vanilla Tor and PCTCP. Despite the fact that PredicTor still performs better in this regard, it loses much of its advantage.

This insight is important for evaluating the suitability of approaches based on model predictive control for congestion handling. Such approaches, like PredicTor, heavily rely on the assumption that their internal system model gives a suitable representation of the real system behavior. What happens in the case of latency is that PredicTor’s predictions about when data will arrive and what size the buffers will have in the future become less accurate with growing link fuzziness. As a consequence, its effectiveness in reducing latency in the network also declines. To a certain degree, this issue could be tackled by extending the system model, including a more complex model for latency as well as an explicit notion of dealing with latency variations in the controller. However, on a conceptual level, the issue of a mismatch between the modeled system behavior and the real behavior cannot fully be avoided. In this regard, traditional approaches may prove more robust against unexpected external influences.

However, when looking at the achieved throughput and fairness, presented in Figures 11 and 12, we can see that a deviation from the system model does not necessarily degrade performance in every regard. As can be concluded from the plots, the achieved throughput and fairness remain relatively unaffected even by large fuzziness values, even less than the traditional approaches. On the one hand, this may be due to the fact that we simulate the distribution of feedback trajectories out-of-band, as discussed before. On the other hand, however, we attribute this to the fact that PredicTor operates on the notion of data rates instead of absolute numbers of packets to be transferred. These rates can be realized by Tor even if data is available later than expected due to higher latency or if there are temporary peaks of data due to inaccurate latency prediction. The controller is called for computing a data transfer schedule in distinct time intervals only. In the meantime, Tor can adhere to the calculated plan and benefit from the enforced properties such as max-min fairness, even if the system model was partly inaccurate. As a result, PredicTor proves itself to be more robust than traditional approaches in these specific regards. Note that, in its current form,
Fig. 11. Impact of link latency deviation from the system model on achieved throughput in random networks with 50 relays. The throughput values are obtained as the sum of all circuits.

Fig. 12. Impact of link latency deviation from the system model on achieved fairness in random networks with 50 relays. Fairness is measured in terms of the fairness index $F$.

PredicTor makes use of TCP for realizing the underlying data transfer. While this design choice was primarily made for simplicity reasons, we now see that it also helps with robustness. If PredicTor also ran its own transport protocol based on its system model, the impact of a system model mismatch might have been more severe. We thus think that it may constitute a promising strategy to combine predictive control approaches with traditional algorithms in a way similar to what we did in PredicTor.

### 5.5 Impact of Traffic Patterns

In order to better understand PredicTor’s behavior with regard to its traffic dynamics, we now focus on how it deals with other traffic patterns. The behavior and effectiveness of every congestion control algorithm clearly also depends on the kind of traffic it is supposed to handle.

In the previous subsections, we considered bulk traffic only. That is, the data to be transferred denotes an infinite stream of bytes. The intention was to analyze the steady state behavior, which provided general insights on PredicTor’s mechanics. At the same time, it enabled us to accurately measure the achieved throughput. This approach, however, is not sufficient for establishing an understanding of PredicTor’s dynamic behavior. Therefore, we consider another scenario with more dynamic traffic, where data streams come and go.

In order to do so, we follow a simple methodology that was put forward in [22] and since then has been applied by a series of publications in this field [23, 40, 43]. The general approach is to
divide the circuits into two groups: on the one hand, a certain fraction of the circuits carries out bulk data transfers, similar to our previous approach; on the other hand, the other circuits are regarded as interactive web circuits. Their behavior is meant to mimic that of a client interactively browsing the web. More specifically, such circuits transfer an object 320 KB in size and wait for a random amount of time (between 1 and 2 seconds) before they repeat. This way, a certain amount of traffic volatility is created. Although this model is very simplistic in nature, we rely on it to establish comparability with previous work in the field. In our implementation, the bulk circuits start first and the web circuits join later at random times. We focus on one representative example for explaining various behavioral aspects that can be observed. In particular, we continue to set the number of relays to 50 and the number of circuits to 300, which corresponds to the mean value between the previous examples for low and high degrees of congestion. Considering even more congested networks would run counter to our goal of simulating interactive circuits because even smaller per-circuit data rates would make bulk and interactive traffic more similar due to the increased transfer times. Moreover, we choose a share of interactive web circuits as 90% to approximate the estimation from previous work [29, 40]. We carry out 25 random repetitions of this simulation scenario and measure the byte-wise latency of data through the network, as before.

Figure 13 presents a CDF plot of the achieved per-circuit latencies over all runs, differentiating between bulk and web circuits, for PredicTor as well as vanilla Tor and PCTCP. The main observation that can be made is that PredicTor achieves low latency for its circuits even in this scenario with 90% web circuits. In contrast, the majority of circuits handled by the traditional congestion control algorithms exhibit clearly worse byte-wise latency. Also, for web circuits, they lead to a long tail of extremely high latency. This is due to the fact that the web circuits join the network when it is already overloaded and contains large queues.

One might have expected PredicTor to perform worse because the short flows give it less opportunity to apply its predictive behavior. However, there are two main reasons why this is not the case. First, even these short flows cover several optimization timesteps of PredicTor; thus, it can, in fact, apply its predictions to some extent. Second, and even more important, this experiment clearly visualizes PredicTor’s second characteristic behavioral trait, apart from predictiveness—its cautiousness or pessimistic scheduling. While vanilla Tor and PCTCP send as much data into the network as possible, PredicTor does so only when the circuits are assigned an appropriate data rate by the optimizer. This, in return, happens only if the network is, in fact, able to promptly process
and forward the data. Put differently, we can again see the trade-off made in PredicTor: it optimizes the latency that payload bytes in the network experience, at the cost of sacrificing throughput, as we have shown in Section 5.3. In the following, we discuss this relationship in more depth, among others.

### 5.6 Discussion

The different steps of our evaluation convey the following overall picture. PredicTor is highly effective at realizing what is explicitly defined within its formal optimization objective. In particular, the improvements it achieves with regard to latency and fairness compared with vanilla Tor and PCTCP are considerable. While this already becomes apparent by looking at absolute measurement values from selected runs, the most remarkable difference lies in its asymptomatic behavior. Unlike vanilla Tor and PCTCP, both metrics do not degrade with growing levels of congestion; rather, they stay nearly constant independent of the level of congestion due to the created backpressure. However, we have also seen that PredicTor achieves lower throughput than the traditional approaches. Therefore, it makes a clear trade-off that is defined by the optimization goal in the controller. Not being able to simultaneously optimize throughput and latency is not a shortcoming specific to PredicTor; rather, it has long been known as an inherent limitation of congestion control algorithms [20]. While the traditional approaches we considered (vanilla Tor and PCTCP) optimize for throughput, PredicTor puts the emphasis on latency instead. Other strategies would include, for example, alternating between these goals over time, as is done by BBR [8].

We also showed that the latency improvement is not an artifact of the lower throughput; rather, it is an achievement of the controller itself. The explicit queue constraints in Equations (25d) to (25f) in the optimization problem enforce low backlog and, thus, a reduced aggressiveness of the generated traffic. As a consequence, we consider PredicTor and similar approaches based on distributed MPC to bear strong potential as the base for novel congestion control mechanisms that achieve performance values and trade-offs that are not yet covered by existing traditional approaches.

Apart from this trade-off, we have seen two major disadvantages. First, like all MPC-based approaches, PredicTor is dependent on the mathematical system model it utilizes for making predictions of the network state. Our evaluation reveals that deviations from this model can severely degrade the performance. Moreover, the consequences of such model mismatches are not necessarily easy to foresee in advance. As an example, we saw that throughput and fairness remained relatively unaffected by growing link latency model errors. We have also seen that the combination of MPC-based approaches such as PredicTor with traditional underlay transport protocols such as TCP can be beneficial with regard to robustness. The second factor that may potentially prove disadvantageous concerns scalability. In our naïve implementation, computational effort and communication overhead grow linearly with the number of participating relays. A multitude of improvement steps could be considered to alleviate or overcome this issue. For instance, we imagine solving only individually reduced optimization problems at each relay instead of the complete optimization problem we presented here. Also, parameters such as data resolution, horizon length, and data representation—including data compression—should be taken into account. Continuing to research such refinements can make MPC-based congestion control schemes very interesting alternatives to existing algorithms.

### 6 RELATED WORK

Efficiently transferring the circuits’ data through the Tor network is far from trivial. Many factors are known to contribute to performance issues in Tor [3]. These include circuit selection [45], local handling of connections at each relay [23], and the transport protocol [42]. Congestion control affects each of these fields. Research has shown that insufficient congestion control is a major factor.
in Tor’s performance problems [3]. Despite years of research on the topic, many of these problems currently remain, also due to the challenging deployment process for fundamental changes to the Tor network [14, 25].

Since Tor is an overlay network, there generally are multiple conceivable approaches towards congestion control. In particular, congestion control could either be carried out end-to-end or hop-by-hop. Operating end-to-end matches more closely the classical notion of congestion control as it is commonly understood for underlay networks. In Tor, this would mean that only the endpoints (client and exit) are involved. In fact, this is how vanilla Tor currently operates. Contrary to many other IP networks, though, reliability is currently implemented in a hop-by-hop manner between Tor relays. Several previous proposals have decided to stick to the paradigm of end-to-end congestion control. For example, UDP-OR [42] tunnels a single TCP connection through Tor using UDP as an underlay. IPPriv [27] follows a similar approach using IPsec. Taking the idea of “stateless” intermediate relays one step further, one could even consider applying active queue management techniques such as CoDel [33] or quality of service approaches (e.g., DiffServ [32] or DPS [37]). The anonymization functionality could even be moved completely to the network stack, as LAP [19], HORNET [9], and TARANET [10] demonstrate. However, there is a common drawback for all of these approaches: since the relays within a circuit may be located all over the world, the resulting round-trip times between the endpoints become very large. As a consequence, the increased feedback loop results in degraded performance [4, 39]. PredicTor takes advantage of the fact that the intermediate relays operate on the application layer anyway; thus, they can be taken into account for congestion control, keeping the feedback loop small and potentially enabling better performance. This strategy has been followed before, for example, by replacing Tor’s very coarse-grained, end-to-end congestion window with a more flexible scheme [1] or even integrating multi-hop congestion control into a tailored transport protocol [40].

On the other hand, PCTCP [2], which uses a dedicated TCP connection between each relay for every circuit, has the potential to be actually deployed in Tor. While PCTCP provides some improvements, for example, in fairness, it still does not provide sufficient congestion control. Other approaches often require changes to the network infrastructure and, therefore, are not directly applicable. These approaches have focused primarily on reusing existing approaches from the networking research for this specific use case. In contrast, our work facilitates recent advances in the field of control technology. Thereby, we open a new perspective for advancing congestion control using interdisciplinary research.

Multi-hop congestion control has been an active research topic in other fields as well. For example, numerous scientific contributions apply suitable schemes in the context of (wireless) mesh networks [26, 36, 47]. However, these have slightly different use cases and premises. For example, in Tor, it would not be acceptable to route around congested areas of the network, as this would put the user’s anonymity at risk. However, in special situations, our approach may also be applicable to these scenarios in some similar form.

The problem of congestion in networks has also been studied extensively from a control theoretical perspective in the past. Previous works include classic linear control [28], including PID [46] and state-feedback LQR control [6]. It is well understood that delay is among the main challenges of controlling the network. More recently, especially optimization-based methods have been applied to the problem with promising results [18, 30]. MPC, as applied in [30], is an advanced control technique that can deal with non-linear systems and explicitly takes constraints into consideration. Its predictive control action is particularly suited for systems with significant delay. Furthermore, MPC has received significant attention as a method for distributed control [11, 31], in which local controllers interact to jointly control an interconnected system. Distributed MPC is often applied to systems with a complex network character, such as transportation systems [15], energy
management [34] or process industry applications [11], for which a centralized solution is prohibitive due to the size of the system or privacy concerns. In order to obtain global properties, local action is often coordinated by exchanging information about predicted future behavior [31].

7 CONCLUSION AND FUTURE WORK

In this work, we proposed a refined version of PredicTor, a novel MPC formulation to tackle the challenge of congestion control in multi-hop overlay networks such as Tor. PredicTor is a distributed approach that relies on exchanging information about the predicted network state between adjacent nodes.

We presented a thorough evaluation of PredicTor’s performance in complex networks. Our results indicate that approaches such as PredicTor that build on distributed MPC for congestion control can, in fact, achieve clear improvements in various regards. The flexibility of tailoring the optimization goal to the exact requirements of a use case makes it possible to realize flexible trade-offs. In PredicTor, we chose to prioritize a strict notion of max-min fairness as well as low latency in the network. As our evaluation shows, PredicTor is able to clearly improve on the status quo in these regards. On the other hand, the trade-off for these benefits is lower throughput.

Our work on using MPC for congestion handling shows the potential of bringing together traditional networking research and modern control theoretical approaches. However, our work is only a starting point for this research direction. Several open issues remain: one important current drawback is the dependency on an accurate system model. If this underlying description of the system, for example, does not capture an unexpected external influence, the advantage of MPC can easily be lost. Another research question that remains unanswered for now is scalability. Our implementation of PredicTor was not optimized in this regard and we did not take communication overhead into account because the resulting goodput ratio is too dependent on the real network conditions (i.e., the absolute data rate). However, the computational effort and communication necessary for exchanging the feedback information currently grows linearly in the number of relays for each node. This puts a natural upper limit on the size of networks that can be handled efficiently. However, for overlay networks that are limited in size, it may prove viable. Future research will have to show whether these disadvantages can be alleviated to enable real-world application.

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