Consolidate Viability and Information Theories for Task-Oriented Communications: The Case of Remote Power Plants

Ozgur Ercetin, Mohaned Chraiti and Rustu Erciyes Karakaya
Faculty of Engineering and Natural Sciences, Sabanci University, Istanbul, Turkiye
Email: {oercetin, mohaned.chraiti, rerciyes}@sabanciuniv.edu

***Abstract*—The next generation of cellular networks, 6G, is expected to offer a handful of exciting applications and services, including holographic communications, machine-to-machine communications, and data sensing from millions of devices. Whether these services come with a Gbps rate requirement or call for massive connectivity, they translate to the need for more spectral resources that are deemed to be scarce and costly. The communications resource should be wisely managed through value-driven approaches that eliminate waste and continuously enhance the communication process. These management principles align with the Task-Oriented Communications (TOC) philosophy. The aim is to allocate the minimum necessary communication resources according to the receiver (actor) goal. In the pursuit of the goal, the receiver may encounter irregularities and unforeseen events, rendering unclear how to build knowledge on the receiver's state and communicate accordingly. Our management approach integrates viability theory and transfer entropy to maintain the actor within a viable space, in contrast to the conventional approaches that help the actor to pass through singular states. By favoring a set of viable states aligned with the receiver (actor) goal and gradually reducing information exchange through knowledge accumulation, our method enhances flexibility and minimizes the risk of the receiver entering a non-viable state, thereby optimizing the communication resource as per the receiver goal. We discuss these theories in the context of TOC and examine their application in the plant process control case.**

***Index Terms*—Task-oriented-communication, viability theory, transfer entropy, remote power plant.**

I. Introduction

Shannon's influential work, which falls under the category of Level A Technical Communications, has provided a strong foundation for groundbreaking advancements in communications and networking. The objective of Technical Communications is to ensure that a sequence of bits is perfectly reconstructed at the receiver. This approach was effective in an era when end devices had limited computational capabilities. However, in the last five decades, the computational capabilities of end devices have grown exponentially. Additionally, the use of specialized artificial intelligence (AI) chips in end-user devices has become more common, enabling the application of modern machine learning algorithms for highly complex calculations. In this respect, discussions have already begun on a paradigm shift from Shannon's Level-A to Level-B (semantic)/Level-C (effective) of communications [1]. Some of the recent works approach the problem from a semantic perspective, i.e., focusing on the conveyed meaning of information. The objective is to reduce the number of bits in transfer by performing *end-to-end* semantic encoding [1]. However, by itself, semantic communications do not capture the time-dependent impact on the receiver. Recent works are increasingly directing their focus toward task-oriented communications, in which the impact of information on the receiver is central to the investigation. In [2], the authors explore the role of fidelity in goal-oriented semantic communication through a rate-distortion approach. Another study proposes an explainable semantic communication that selectively transmits task-relevant features for improved transmission efficiency and robustness against semantic noise [3]. In another work, the authors investigate the possible cooperation between the senders and receivers to minimize semantic error (i.e., belief efficiency) and achieve a goal via curriculum learning [4].

This paper discusses the design of task-oriented communications (TOC) pertaining to *the afterword impact of the received data on the end-user's actions*. There is no doubt that the receiver must properly decode/interpret the received data before taking a possible action; however, the effect of the interpretations on the receiver's actions differentiates TOC from semantic communication. The main utility of TOC is to continuously assess the need/goal of the receiver and its capability, then accordingly assign the minimally sufficient communication resource. For the majority of case scenarios, **the receivers (actors) goals outlines are flexible to a certain extent, and their actions are *robust* such that they do not suffer from limited irregularities.** The receiver's robustness results from the processes' characteristics or the AI-empowered knowledge base that takes action. Whether or not the actor has strict goal outlines or is robust to irregularities, these quantities have to be understood, analyzed, and exploited in an autonomous (closed-loop) fashion for a communications approach that delivers values as per the actor's object.

TOC leverages continuous understanding/assessing of the actors' goals, capabilities, and environment to deliver adequate communications resources. In light of irregularities and unforeseen events, ranging from the actor's inability to execute control-unit directives with precision (internal impairment) to those caused randomly by nature (external impairment), the viability theory [5] provides an adequate framework for TOC. This theory defines the viable space, also known as the viability kernel, within which an actor can evolve toward its goals while preserving important qualities such as adaptation, stability, confinement, homeostasis, and tolerance. The larger the kernel size, the more tolerant the actor is to errors, including those resulting from delayed instructions, thereby reducing further resource utilization.

Although the viable space can be derived through optimization or machine learning, it differs conceptually and in terms of its core objective. The viability theory offers more thorough solutions, as it assesses the risks of adopting a solution in the presence of uncertainty. In contrast, optimization approaches typically determine the best strategy, often overlooking close-performing solutions in which the actor remains operative. As a result, the actor may need to continuously seek support from the control unit, in case it is impelled outside the thin-line solution.

The viability kernel encompasses the set of viable states, providing actors with room for action and decision errors, enabling more autonomous task-execution. The actor resorts to the control-unit only when events require more refined solutions, computationally demanding decisions, and/or more trained models. The viability kernel width determines the resilience degree to unknown disruptions. Understanding the viability kernel allows to derive the appropriate communication rate required to convey minimum-sufficient directives and knowledge. As per the viability theory, the objective of TOC is to dynamically analyze the environment and actor state to develop strategies that maintain a safely-large viable space.

For example, an efficient communications strategy may involve adopting a viable path with a low communication rate, instead of a shorter path that requires channeling high-rate instructions. The viable space depends largely on the actor's capability and knowledge, which can be continuously accumulated from the past. To measure the rate of meaningful information flow over time while knowledge continues to be accumulated, we suggest using Transfer Entropy (TE) [6]. This measure quantifies the knowledge transfer between communicating parties, enabling them to assess and adjust their communication strategy.

Our paper contributes by proposing a novel management approach for communication resources in 6G networks, integrating viability theory and transfer entropy. This approach aligns with the TOC philosophy, aiming to allocate minimal necessary resources based on the receiver's objectives and gradually reduce information exchange through knowledge accumulation, as demonstrated in the context of plant process control in Section-IV. Other motivating use cases are stated in the Section-II and we propose our framework in Section-III with mathematical preliminary on viability and information theory. Lastly, in Section V, we are giving insights into future research directions from computational, performance, and protocol perspectives in the evolving landscape of 6G networks.

II. Motivating Use Cases

In this work, the analysis primarily pertains to developing a viability theory based TOC approach in the context of a remote power plant. Nonetheless, we briefly discuss some other timely use cases that motivate the utility of viability theory.

A. Multi-sensory and holographic telepresence

Consider the case of replicating the sense of touch at a remote location [7]. The receptors on the hand/feet from the brain are about 1.5 and 2 meters away, and the speed at which a sensory point transmits data is around 30 m/s. Accordingly, the maximum delays of signals are 0.038s and 0.067s [8]. A human can detect temperature differences with a 0.02°C resolution in $5-45$°C range. Transmitting temperature and pressure information to replicate the sense of touch, sampled at 50 Hz, requires bit rates of up to 880 Mbps with minimal delays. In this context, we envisage the rule of Viability theory to aid in determining communication bit rates and delays sufficient for a human-like sensing experience, considering the brain's ability to interpolate missing data. Meanwhile, transfer entropy helps identify information redundancies and dependencies between sensory points, facilitating the design of efficient closed-loop systems for multi-sensory telepresence applications.

B. Autonomous Vehicles

In the context of autonomous vehicles prioritizing both travel efficiency and safety, a cloud-based control-unit supports the vehicle by continuously adjusting communication rates based on the dynamic evaluation of factors such as environmental conditions, vehicle capabilities, and control-unit expertise. The viability approach is capable of ensuring safe navigation while considering system constraints like delay and battery life. Communication rates are adapted to maintain a broad viable space, with higher rates near the viability boundary. As the environment evolves, the system reassesses risks, enhancing vehicle autonomy, and optimizing communication rates, leading to a task-oriented communication strategy.

C. Remote Power Plant

The remote power plant serves as another example where maintaining the plant's operation within a safe range is the primary objective of the control unit [9]. The state of the power plant is defined by its temperature and pressure. The main function of the control unit is to provide directives to the power plant regarding heat supply and the displacement rate of a pneumatic piston, with the primary goal of keeping the plant's state (heat and pressure) within a predetermined safe range. While the plant must remain continuously connected to the control unit for state monitoring and directive purposes, abnormal states occur sporadically and do not persist indefinitely, allowing for the potential conservation of communication resources. In the context of viability theory, one can define the viable space of the plant's states that do not necessitate intervention from the control unit, communicating only when necessary. This approach suggests saving on communication resources and aligns with the principles of TOC.

D. The statement for task-oriented communications

In the listed examples, the goal is not to support continuous streaming of timely packets from the sensors or minimize the mismatch between the actual and estimated data. Instead, it is to design a system that functions similarly to a human communication/processing system, which is task-oriented and aligns with the viability theory principle. The primary aim is to allocate resources to communicate changes outside the viable space to ensure a genuine and swift response from the system. For example, a person responding to significant changes in temperature/surface tension, a doctor responding to changes in a remote patient's body, or an autonomous factory responding to anomalies in machines' states.

TOC solutions typically answer two fundamental questions: **1) How can we communicate effectively while ensuring proper operations of the end-system? 2) What is the optimal data rate given a task to accomplish?** Our TOC framework incorporates two key concepts to answer these questions: **1) The viability theory to identify and expand the actor's space of options to ensure robust operation. 2) The transfer entropy to measure knowledge accumulation and utility of communications while executing current and future tasks.** The following is an overview of these concepts.

III. Proposed Framework

A. Viability Theory

Viability theory is a field of mathematics that studies the steady evolution of dynamic systems under state constraints

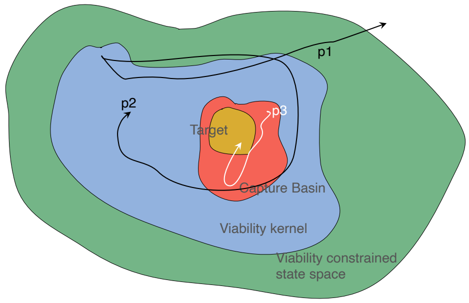


Fig. 1. Viable control.

and in the presence of uncertainties [5]. It gives directives on how to effectively regulate the evolution of actors given uncertain events. The viability theory yields a set of solutions/states of a dynamic system, referred to as its viability kernel (the main elements forming the viable space are depicted in Fig. 1.) The viability kernel is defined as the set of states in which an actor can operate and evolve within normal/safe parameters given a certain rate of guidance from the control unit, i.e., communication rate. As the actor evolves, the communication rate may increase to supply the actor with more knowledge. The latter occurs when the actor is impelled to be on the boundary of the viability kernel and seeks to restore its viability. The fact that the actor is aware of the states helps to improvise and steer the communication rate with the control unit. Also, as a part of the viability theory framework, the concept of a capture basin will be used to deal with delay constraints. A capture basin is a set of viable states that can achieve a specific task within a predetermined time frame.

Let us consider a smooth nonlinear dynamic system F with bounded control such that:

$$\dot{x}(t) = f(x(t), u(t)), \quad u(t) \in [U], \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the state vector, $u(t) \in \mathbb{R}^m$ is the control input, $[\cdot]$ stands for interval vector, and $[U] = \left[[\underline{U}_1, \bar{u}_1], \ldots, [\underline{U}_m, \bar{U}_m]\right]^T$ is the control constraint. Denote $\varphi(\tau, x(0), u)$ as the state of the system F at time τ with initial state $x(0)$ and control input $u(t)$. The union of the states forms the trajectory:

$$\varphi([0, \tau]; x(0), u(t)) = \bigcup_{t \in [0,\tau]} \varphi(t; x(0), u(t)) \tag{2}$$

Note that the trajectory is a set of state vectors with respect to time.

Consider $K \subseteq \mathbb{R}^n$ to be the space of viable states and $C \subset K$ to be the target states as indicated in Fig. 1. Namely, feasible states form a viable set, while the target states are those where objectives are met within the feasible set. Then, the capture basin is defined as $\mathrm{Capt}_F(K, C)$, and it refers to the set of the viable current states in K, from which there exists at least one viable trajectory that can reach the target C within a predefined time window τ, where $t \in [0, \tau]$:

$$\mathrm{Capt}_F(K, C) = \{x(0) \in K | x(\tau) \in C, \forall x(t) \in K\} \tag{3}$$

The viability-based approach to TOC targets identifying a viable kernel of the dynamic system acting in a specific environment while considering existing constraints, communication limitations, state uncertainties, and actor capabilities. The system then adjusts communication resources in a closed-loop to maintain viability. The size of the viable kernel particularly depends on the actor's capabilities, which may be enhanced to reduce communication resource usage further.

B. Transfer Entropy

Transfer entropy (TE) is a measure used to quantify the flow of information between random processes by analyzing causality from the generalized Markov property [6]. Transfer entropy quantifies the impact of the control unit decisions/directives at the previous $(N-1)$ time slots, denoted as $u((N-k)T_s) \in [U]$ ($N \in \mathbb{N}, k \in 1..N$, and $T_s \in \mathbb{R}^+$), on the state of the actor at the Nth time slot $x(NT_s)$. The upper limit of the transfer entropy is the directed information flow from a length N sequence $\boldsymbol{u}^N = \{u(T_s), u(2T_s), \ldots, u(NT_s)\}$ to $\boldsymbol{x}^N = \{x(T_s), x(2T_s), \ldots, x(NT_s)\}$, which in turn is defined as follows [10]:

$$\begin{aligned} \mathcal{D}I\left(\boldsymbol{u}^N \to \boldsymbol{x}^N\right) &\doteq H\left(\boldsymbol{u}^N\right) - H\left(\boldsymbol{u}^N \| \boldsymbol{x}^N\right) \\ &= \sum_{n=1}^{N} I\left(\boldsymbol{x}^n; u(nT_s) \mid \boldsymbol{u}^{n-1}\right), \end{aligned}$$

where $H\left(\boldsymbol{u}^N \| \boldsymbol{x}^N\right)$ is the entropy of $\boldsymbol{u}^N$ causally conditioned on the sequence. $\boldsymbol{u}^n$ stands for control input between time slots 1 and n. By combining transfer entropy and viability theory, we can measure the flow of information between past and present/future events or actions. The actor-centric operation allows for customization based on diverse end-user perceptions and applications. The actor's behavior relies on accumulated and inherited knowledge, and the upper limit of this knowledge can be represented by the information content derived from the history of two random processes: *the control action and actor state random processes*.

C. Viability and Information Theories for Task-oriented Communications

Viability theory is a framework for examining possible states and transitions between these states with the objective of identifying those states that are "viable". These states may include adaptation, stability, confinement, homeostasis, tolerance, etc. The choice of criteria depends on the actor, the actor's capabilities, and the environment. These factors may change over time as the actor's state evolves. In the context of TOC, the viability kernel is discussed as a tool to help an actor achieve its objective with minimal remote support from a decision unit. The control unit starts with more knowledge than the actor, using trained models, experience, and statistics. However, unpredictable environments and actor responses can lead to unexpected events such as glitches or disturbances.

As seen in Fig. 2, the actor and the control unit communicate in a closed loop to dynamically identify the viable kernel and their appropriate communication rates. When stringent constraints are involved, it is more suitable to consider the capture basin instead of the viability kernel. This allows, for instance, a drone with delay constraints to consider the fastest path, even if it involves more communication resources. Hence, viability theory provides a structured way to model adaptivity, establish decision policies, and determine the viability kernel based on the actor's ability. Note that actors are able to learn from past decisions and use this knowledge to improve decision-making intelligence through knowledge transfer. As time passes, the actor becomes more self-sufficient, leading to a decrease in the need for communication. This is where the concept of transfer entropy comes into play, quantifying the knowledge transfer between the control-unit decisions random process, actor state random process, and the probabilistic model that binds both processes.

Our framework utilizes the in-the-loop (ITL) transmission rate metric [11]. This metric can be defined as:

$$\begin{aligned} R_{ITL}^{N} &\doteq \frac{1}{N}\sum_{n=1}^{N} H\left(\boldsymbol{u}^{n} \mid \boldsymbol{u}^{n-1}, \mathrm{x}^{n-1}, \mathrm{p}_{1}^{n}\right) \\ &= \frac{1}{N} H\left(\boldsymbol{u}^{N} \mid \boldsymbol{x}^{n}, \mathrm{p}^{n}\right) + \frac{1}{N}\mathcal{D}I\left(\boldsymbol{u}^{N} \rightarrow \boldsymbol{x}^{N} \| \mathrm{p}^{N}\right), \end{aligned}$$

where $\mathcal{D}I\left(\boldsymbol{u}_{1}^{N} \rightarrow \boldsymbol{x}^{N} \| \mathrm{p}^{N}\right)$ is directed information from $\boldsymbol{u}^{n}$ to $\boldsymbol{x}^{n}$ causally conditioned on the sequence p^{n} of the probabilistic model of the dynamic system.

The proposed TOC system setup is depicted in Figure 2. To ensure the system's continuous operation, it is imperative to consider the bidirectional flow of information between the random actor process and the control process. The encoder and decoder can reduce transmission rates by consulting the viability kernel to find optimal action. Following the work in [5], we frame the problem as the minimization of a valuation function, denoted as $\mathbf{V}$, over a finite horizon within capture basins, which is defined as follows:

$$\begin{aligned} \mathbf{V}(T, x) &= \inf_{(x(\cdot), u(\cdot)) \in \mathcal{P}(x)} \left(\mathbf{c}(x(T)) + \int_{0}^{T} \mathcal{L}(x(\tau), u(\tau)) d\tau\right) \\ &= \inf_{(x(\cdot), u(\cdot)) \in \mathcal{P}(x)} \left(\mathbf{c}(x(T)) + R_{ITL}^{T}\right), \end{aligned} \tag{4}$$

where $\mathcal{P}$ is the evolutionary system generated by (1), $\mathbf{c}$: $\mathbb{R}^{n} \mapsto \mathbb{R}_{+}$ is the final state cost function and transient state cost function, often called a Lagrangian, i.e., defined as $\mathcal{L} : \mathbb{R}^{n} \times \mathbb{R}^{m} \mapsto \mathbb{R}_{+}$. The choice of Lagrangian for control mainly depends on the system's characteristics and the objectives that must be met. Therefore, to determine $\mathcal{L}$, the ITL transmission rate is taken into account by discretizing the time horizon [0,T] as shown previously. The final state cost is the following:

$$\mathbf{c}_{\infty}(t, x) := \begin{cases} \mathbf{c}_{1}(x) & \text{if} \quad x(t) \in \operatorname{Capt}_{F}(K, C) \\ \mathbf{c}_{2}(x) & \text{if} \quad x(t) \in K \\ +\infty & \text{if not} \end{cases}. \tag{5}$$

Note that the variables $c_1(x)$ and $c_2(x)$ take the values 0 and 1, respectively, representing the communication cost. If the viability kernel is large or the current state is distant from the boundary, the probability of the system becoming non-viable is low. Moreover, the decoder does not depend heavily on the encoder for viable actions; thus, state transition flow rates can be minimized. Also, note that the viability kernel is dynamic since the control policy evolves with accumulated knowledge.

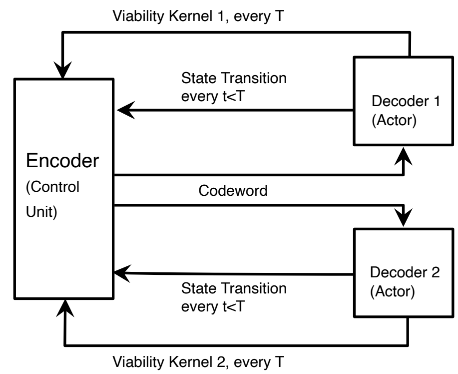


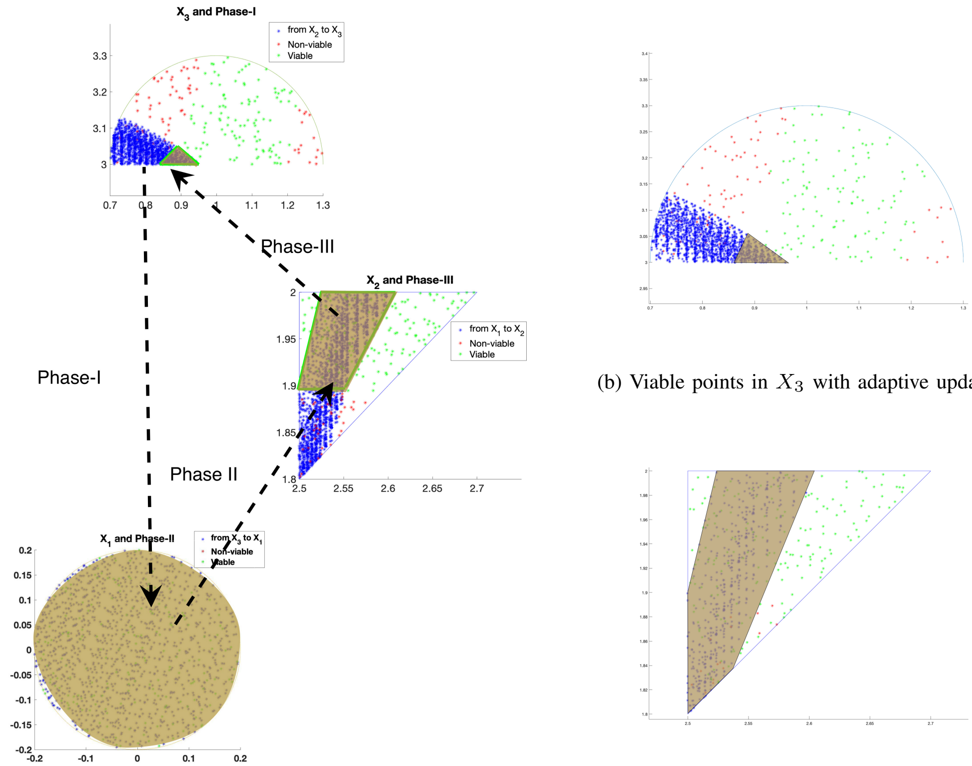
Fig. 2. Proposed framework to ensure safe and successful operation when a control unit communicates with two different actors. As knowledge is transferred, we anticipate that actors will require fewer updates on their state transitions, and hence, the control unit will provide fewer control directives.

IV. An Illustrative Case Study: Remote Power Plants

We demonstrate the distinguishing features of viability theory-based TOC policies via a dynamic control example taken from [9]. We consider the case of the plant (actor) remotely operated by a control-unit similar to the case of the Factory-of-the-Future (FoF). The plant has the capability of sensing the data and communicating them to the control-unit and adjusting the system functioning according to the control-unit directives with reasonable precision, but not free of error. Nonlinear differential equations characterize the plant dynamics. The process requires cycling the plant repeatedly through three operating points. The process is *robust* so that it is sufficient to visit some specified neighborhoods of these operating points. The plant is described with state variables; the temperature of the plant and its pressure. Their units of measurement are normalized so that $(0,0)$ represents ambient conditions. There are two control inputs, i.e., the rate at which heat is supplied to the plant and the rate at which a pneumatic piston is displaced.

The plant operating points are depicted in Fig. IV, $\overline{X}_1 = (0,0)$, $\overline{X}_2 = (2.5,2)$, and $\overline{X}_3 = (1,3)$. The operational process is robust; hence, it suffices to be in states in specified neighborhoods, denoted by X_1, X_2, and X_3, respectively. The plant process must visit three states' levels cyclically in order, namely, X_1, X_2, then X_3. Operating the plant involves three control phases. In Phase-I (respectively, Phase-II and Phase-III), control inputs are fed to the system to reach state X_1 (respectively, X_2, X_3). To elaborate, let us consider that the plant is operating in Phase-II. The control law of this phase must move the plant state from a first state level (at a point X_1) to some point X_2 in the second state level. An off-line processing approach is typically used to synthesize state feedback control laws that move the plant state from one operating point to the next [9].

The plant's simulation results are depicted in Fig. 3a. The system state and corresponding control input are updated every 0.1, 0.05, and 0.05 time units in Phase-I, Phase-II, and Phase-III, respectively. The green regions depict the viable kernels



(a) Fixed update

(b) Viable points in X_3 with adaptive update.

(c) Viable points in X_2 with adaptive update.

that are around the ideal states. Starting from any point in a green region, the plant will continually and cyclically run (remains viable) if adequate decision controls are taken. We observed that the TOC policy has a direct impact on the viability of the process. For instance, we experienced a change in the width of the viability kernel (green region) by the simple fact of altering the state/control update frequency, i.e., TOC rate. For low rates, the width of the viability kernel decreases. It is crucial to monitor the plant with a communication rate high enough for proper functioning but low enough to save resources. This example highlights a common issue that numerous FoF use cases may encounter.

We design an adaptive TOC update policy that infers an adequate TOC rate according to the position of the state within the admissible region. First, we generate a set of 50 priors for each X_n, considering fixed update intervals. We observe the trajectories in each phase and identify the viable states. Suppose both viable and non-viable priors fall within a circle centered on one of the prior states. This state is at the edge of the viability kernel, meaning that it is more likely for a trajectory starting from this state to end up being non-viable. To increase the size of the viability kernel, a smaller update interval is scheduled. In Fig.3b, and 3c, green-colored regions refer to the points in X_3 and X_2 that allow the system to run swiftly and properly. As shown, by adopting a TOC policy, the viability kernel around X_2 has significantly increased, and slightly increased for X_3, without increasing the average communication rate. Furthermore, **the proposed TOC policy decreased the communication rate by 12% in Phase-III, and by 14% in Phase-I.**

TABLE I

TRANSFER ENTROPY (BITS) BETWEEN THE SYSTEM STATES AND CONTROL INPUT DURING PHASE-II. RTRANSFERENTROPY PACKAGE IS USED TO CALCULATE TE FROM THE STATE AND CONTROL TIME-SERIES DATA.

Update period	Transfer Entropy (state $\rightarrow$ control input)	
	Temperature $\rightarrow$ Heat supplied	Pressure $\rightarrow$ Piston displacement
0.1	0.168	0.014
0.075	0	0.0035
0.05	0	0.0007

We have observed that the benefit obtained by increasing the communication rate varies depending on the system parameters. To further investigate this, we have calculated the transfer entropy between the state and control processes in Table I. From the results, we can conclude that updating the temperature state more frequently than once every 0.1-time unit yields no additional valuable information. Therefore, designing a customized policy for each system parameter could potentially enhance the efficiency of the TOC.

The process runs cyclically in the counter-clockwise direction. At the end of each control phase, we mark in green the points in an initial level eligible as starting points to go to the next state level if adequate control actions are applied. Meanwhile, the blue points label viable points at a given state level after completing a phase. The non-viable states are colored in red. For example, consider the Phase-II control actions so that the system goes from a state X_1 in the first level to a state X_2 in the second level. The intersections of green and blue points represent those points that enable the process to be repeated continually, and we mark this region in yellow color.

V. Conclusion

This article discusses a novel approach for TOC, utilizing viability theory to enhance communication efficiency. We stressed that the requirements for envisaged 6G applications would be extensive; meanwhile, the spectrum resources remain scarce and costly. By harnessing viability theory, we can devise an end-to-end TOC framework that is robust against unforeseen events. We provide a framework on how to integrate this theory into TOC and apply the solution to an academic example. The results demonstrated a reduction in the communication rate while ensuring the steady progression of the actor toward its goal across viable states.

VI. acknowledgment

This work is supported in part by Tübitak under grant 122E497. This project has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Sklodowska-Curie grant agreement No 101108094.

References

[1] E. C. Strinati and S. Barbarossa, "6G networks: Beyond Shannon towards semantic and goal-oriented communications," *Computer Networks*, vol. 190, p. 107930, 2021.

[2] P. A. Stavrou and M. Kountouris, "The role of fidelity in goal-oriented semantic communication: A rate distortion approach," *IEEE Transactions on Communications*, pp. 1–1, 2023.

[3] S. Ma, W. Qiao, Y. Wu, H. Li, G. Shi, D. Gao, Y. Shi, S. Li, and N. Al-Dhahir, "Task-oriented explainable semantic communications," *IEEE Transactions on Wireless Communications*, pp. 1–1, 2023.

[4] M. K. Farshbafan, W. Saad, and M. Debbah, "Curriculum learning for goal-oriented semantic communications with a common language," 2022. [Online]. Available: https://arxiv.org/abs/2204.10429

[5] J.-P. Aubin, P. Saint-Pierre, and A. Bayen, *Viability theory: New Directions*. Berlin, Germany: Springer, 2011.

[6] T. Bossomaier, L. Barnett, M. Harré, and J. Lizier, *An introduction to transfer entropy: Information flow in complex systems*. Cham, UK: Springer, 2016.

[7] Y. Gao, X. Wei, J. Chen, and L. Zhou, "Toward immersive experience: Evaluation for interactive network services," *IEEE Network*, vol. 36, no. 1, pp. 144–150, 2022.

[8] T. Kim and S. Park, "Equivalent data information of sensory and motor signals in the human body," *IEEE Access*, vol. 8, pp. 69 661–69 670, 2020.

[9] A. Deshpande and P. Varaiya, "Viable control of hybrid systems," in *Hybrid Systems II*, P. Antsaklis, W. Kohn, A. Nerode, and S. Sastry, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 1995, pp. 128–147.

[10] O. Ercetin, "Computational and communication aspects of digital twin: An information theoretical perspective," *IEEE Communications Letters*, vol. 27, no. 2, pp. 492–496, 2023.

[11] M. Derpich and J. Ostergaard, "Directed data-processing inequalities for systems with feedback," *Entropy*, vol. 23, p. 533, 04 2021.