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Distributed Optimal Control for Consensus in Multi-Agent Networked Systems Under Uncertainty

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Abstract
Communication represents one of the main practical limitations in distributed multi-agent systems. While a consensus can potentially be rapidly reached through a constant information exchange, such a method may be unrealistic for wireless embedded robotic and sensor networks, where bandwidth and power are significantly limited. In this regard, event-triggered and self-triggered techniques have gained attention as noteworthy alternatives to the conventional periodic solution. Consider a probabilistic approach in the form of a state-dependent Poisson process that triggers communication events. In lieu of displacing the theory of event-triggered control, a clever adaptive intensity is proposed that escalates as disagreement grows and tapers off as the nodes reach consensus. The adaptive communication mechanism is integrated with a linear consensus controller and modelled as a stochastic hybrid system with continuous plant dynamics and random sample-and-hold resets. To facilitate the connection between probabilistic communication and mean-square consensus, a quadratic stability method is used, whereas the expected number of communications acts as a measure of communication cost. Numerical research with five, 10, and 20 single-integrator agents are presented for a connected network with uncertain multiplicative parameters.A trade-off between performance and communication rate is demonstrated. For five agents, an increase of the minimum Poisson intensity from 0.2 to 3.0 reduces the integrated disagreement from 4.94 to 2.17 while raising the number of communication events from about 37 to 313. At a practical operating point with minimum intensity of one, the adaptive mechanism exhibits a final disagreement of about 2×10^{-4} with 120 communication events compared to about 245 events for a fixed intensity approach. The results indicate that adaptive Poisson communication effectively and significantly reduces the number of transmissions without a significant expense in performance, although the degree of reduction depends heavily on the minimum rate and number of agents. Thus, the proposed probabilistic communication mechanism is interpreted as an additional degree of freedom that can be tuned rather than a purely stochastic phenomenon.

Keywords: Multi-Agent Systems; Consensus Control; Distributed Control; Poisson Process; Event-Triggered Communication; Stochastic Hybrid Systems; Communication Efficiency; Uncertain Systems.

1. Introduction

Multi-agent systems have become the most important paradigm for the study of coordinated behaviour in autonomous vehicles, mobile robots, sensor networks, distributed energy systems and other networked cyber-physical systems. The premise is deceptively simple: every agent has only local information, but the group, through communication with neighbouring agents, should accomplish a task that is too difficult or inefficient for an individual agent to perform on its own. Consensus is among the simplest such problems in that it requires the states of interacting agents to reach a common value without the aid of a central coordinator. Early results linked the nature of local interaction rules, graph connectivity and the achievement of consensus, while later developments

related the theory of consensus to formation control, distributed estimation, synchronization and cooperative robotics (Jadbabaie et al., 2003; Fax & Murray, 2004; Olfati-Saber et al., 2007).

The standard formulation of the consensus problem presumes that adjacent agents are able to share information at any moment the controller demands it. Such a presupposition turns out to be progressively more limiting as the population of agents expands, or when the communication medium is also used by additional services. Within an actual network,communication lays claim to spectrum, draws upon energy, generates latency, and can find itself in contention with other devices. Consequently, sampling at periodic intervals gives rise to a fundamental incongruity: the network is compelled to transmit at a constant rate even at times when the state already lies near consensus. This difficulty gave rise to event-triggered and self-triggered control schemes, in which communication is aligned more intimately with what the control system requires.(Tabuada, 2007; Heemels et al., 2012)

Over the decade that followed, event-triggered consensus became a large area of study. As surveyed by Ding et al. (2018) and Nowzari et al. (2019), major research questions concerned reducing the number of communications, avoiding unnecessary transmissions, dealing with imperfections in the information, and showing the connection between the triggering mechanisms and convergence. Also of interest are the adaptive and stochastic versions. For example, Xie (2016) combined an adaptive consensus control law with event-triggered communication, while further studies considered stochastic multi-agent systems, constraints, adaptive triggers, and sampling (Xie, 2016; Li et al., 2022; Wu et al., 2025).

This work differs in that there is a departure from an observation. For many real-world networks, the point in time at which the opportunity for communication is becomes available is not subject to a deterministic influence. However, intermittent transmission timings can be introduced naturally by wireless contention, random access, packet creation, computational delay, duty cycling, and asynchronous hardware. A Poisson process is a convenient mathematical model for generating such random events. However, most other forms of variation are in themselves not control solutions; if communication were created in the absence of the state, the system would either waste transmissions in mild disagreement or conversely be unable to communicate under extreme disagreement. The fundamental idea being explored in this paper is therefore to make the Poisson intensity dependent on the state.

However, this distinction is important because the KFe-based consensus under Poisson processes in Lamperski and Papachristodoulou (2014) directly studied multi-agent systems with stochastic clocks induced by Poisson processes and LMI-based conditions were derived for second-moment stability and consensus.It should be noted, therefore, that this work does not claim to be the first one using a Poisson process in consensus control. What is studied here is a communication protocol that makes the Poisson intensity agree with the current disagreement among the agents. The problem to be solved is thus a communication allocation problem: when the coordination is weak, the network should communicate more often, and conversely, it should communicate less often when the team is already close to a consensus.

This particular view might add another layer of connection to the recent efforts of communication-and-control co-design. Ghatak et al. (2025), for example, already incorporated wireless control and communication in a joint way using Poisson point-process models in a communication-control setting. It is shown in their work how increasingly important it is to include communication decisions as an integral part of the control problem rather than considering them as a fixed service external to the control design.The present work goes back to a different setting, which involves not optimizing channel access in a spatial wireless network, but directly adjusting the communication rate of each individual consensus agent based on its local discrepancy.

Accordingly, a conservative objective is used in this paper, but one that is potentially useful. develop an adaptive, state-dependent Poisson communication mechanism, embed it into a distributed consensus controller, formulate the closed-loop as a stochastic hybrid system, and evaluate the communication-consensus trade-off numerically. The numerics are presented such that no positive reduction in communication is naively interpreted as a positive gain. They in fact show that an overly ambitious reduction in communication actually resulted in inferior consensus quality. And this naturally points to the existence of a minimum level of communication that should be used, consistent with the consensus quality that is needed.

2. Related Work and Research Motivation

Consensus theory is, to some extent, heavily reliant upon graph theory. The 'vertices' of a graph correspond to each agent, while 'edges' represent whether there is an information path between them. The link between network topology and the emergent collective dynamics is provided by the graph Laplacian, where the most crucial eigenvalue to understand is the second-smallest, or the so-called algebraic connectivity, as this measures how well-connected the network is, and explicitly appears in many conditions for consensus convergence (Fax & Murray, 2004; Olfati-Saber et al., 2007). In the subsequent years, graph-theoretic approaches to multi-agent control have become a standard method by which formation, synchronization, distributed estimation, and consensus are analyzed (Mesbahi & Egerstedt, 2010)

Standard consensus algorithms assume that data from neighbouring agents is always available. Under this assumption, a simple proportional coupling rule can lead to a decay of the disagreement in the Laplacian spectrum. For an in-depth treatment of distributed consensus and its applications to cooperative vehicles, see Ren and Beard (2008), while for the fact that distributed information exchange can also be embedded into network optimization see Nedi and Ozdaglar (2009).The control scheme, which forms the basis of this work, is provided by these advances.

Constraints dictated by communication lead to a second branch of research. Tabuada (2007) developed a control architecture, now in widespread use, where control updates are not clock-driven, but initiated whenever the controller decides that the latest measurement or control computation is due.Heemels et al. (2012) later proposed event- and self-triggered control for networked systems with constrained resources and elaborated how control performance is linked to communication cost.

Further work on periodic event-triggered control and hybrid-system formulations demonstrated how communication policy can be directly embedded into the analysis of system stability (Heemels et al., 2013).The same idea has become the basis of a lot of literature in the multi-agent consensus literature. Ding et al. (2018) reviewed event-triggered consensus, and Nowzari et al. (2019) looked at the broader set of issues of imperfect information, communication constraints, triggering rules, and distributed implementation.More recent studies have extended the ideas to stochastic systems, adaptive triggering, non-linear dynamics, actuator saturation, and adaptive sampling (Li et al., 2022; Wu et al., 2025).

This work straddles the boundary between deterministic event-triggered control and communication that is fully stochastic. Instead of a deterministic boundary having to be crossed, each agent continuously varies the rate of a stochastic communication process. As such, the methodology can be interpreted in probabilistic terms. A large disagreement does not necessarily require a transmission immediately, but increases the probability that a transmission occurs. Similarly, a small disagreement does not necessarily inhibit communication fully, as a nonzero minimum intensity is maintained. This latter property is useful for avoiding a communication scheme getting stuck in the vicinity of consensus.

3. Methodology

3.1 Multi-agent model

Consider N agents whose dynamics are represented by

$$\dot{x}_i = Ax_i + Bu_i + Dw_i,$$

where $x_i$is the state, $u_i$is the control input, and w_i represents an external disturbance. Model uncertainty can be represented by perturbations in the system matrices, although the numerical case study uses a simpler multiplicative uncertainty model. The communication graph is represented by an undirected connected graph $G = (V, E)$, with adjacency matrix $A_G$and Laplacian L.The consensus of the group is designed to bring the disagreement vector to zero. In reality, this means that despite the fact that the individual agents may be able to keep a shared motion or shared state, the disagreements of neighbouring as well as non-neighbouring agents should disappear. This formulation is the same as the usual graph-based consensus found in multi-agent systems.The distributed controller considered here is based on the mismatch between the local state and the most recently received neighbour states. Each agent maintains a stored estimate of the state of each of the neighbours. This must be done since communication is no longer continuous.

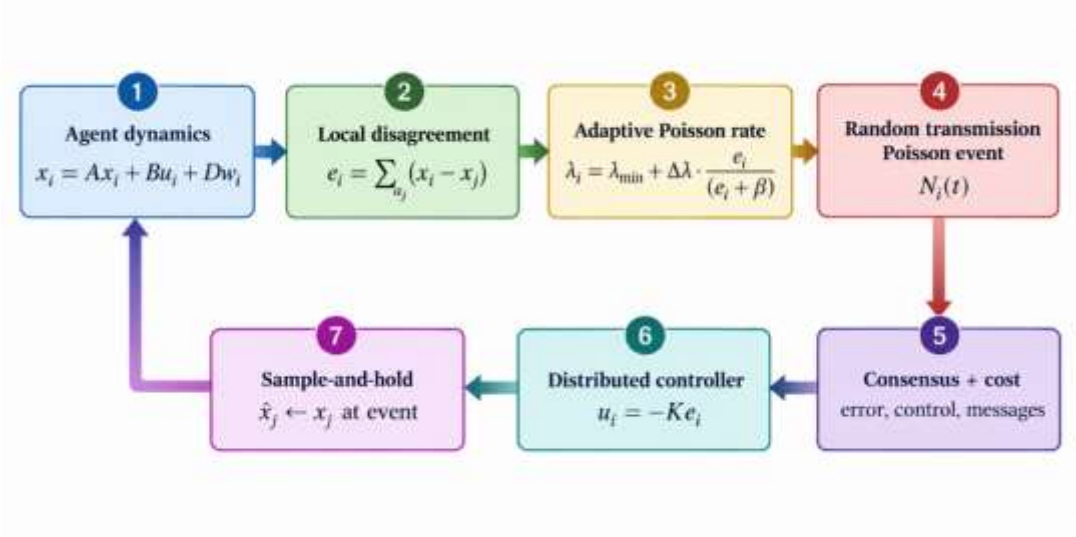


Figure 1. Adaptive Poisson-driven distributed consensus architecture.

Figure 1. provides a synopsis of the architecture that has been put forward. Rather than constituting four separate components, the controller, the disagreement measure, the communication intensity, and the state-holding mechanism collectively constitute a single feedback loop. Such a reading aligns with the wider body of scholarship on event-triggered control, in which decisions pertaining to communication and to control are progressively conceptualized as design variables that are coupled with one another.

3.2 Adaptive Poisson communication

Let $e_i$denote the local disagreement available to agent i. The proposed communication intensity is

$$\lambda_i = \lambda_{\min} + (\lambda_{\max} - \lambda_{\min}) \frac{e_i^2}{e_i^2 + \beta}.$$

Only the behaviour of this relationship is important for the present discussion. When $e_i$is large, the fraction approaches one and the communication intensity approaches $\lambda_{\max}$. When the local disagreement becomes small, the intensity approaches $\lambda_{\min}$. The parameters therefore have intuitive meanings. $\lambda_{\min}$determines the minimum communication activity, $\lambda_{\max}$prevents excessive transmission rates, and βcontrols how quickly the mechanism moves from low to high communication activity.

The communication event process $N_i(t)$is assumed to have instantaneous intensity $\lambda_i(t)$. Over a sufficiently small interval Δt, the probability of one communication event is approximately $\lambda_i(t)\Delta t$. Consequently, the expected number of communications during a finite horizon is the integral of the intensity. In a finite time horizon, the expected number of communications is the integral of the intensity. The implication of this is that, from an analysis point of view, the approach is able to obtain the cost of communication in an explicit form rather than obtain it as a function of the trigger threshold.

The state received by an agent is held between communication events. If agent $i$transmits its current state, neighbouring agents update their stored value of x_i. Otherwise, they continue using the previous value.It is this sample-and-hold structure that makes the proposed system a stochastic hybrid system rather than a typical deterministic differential equation.

3.3 Stochastic-hybrid interpretation

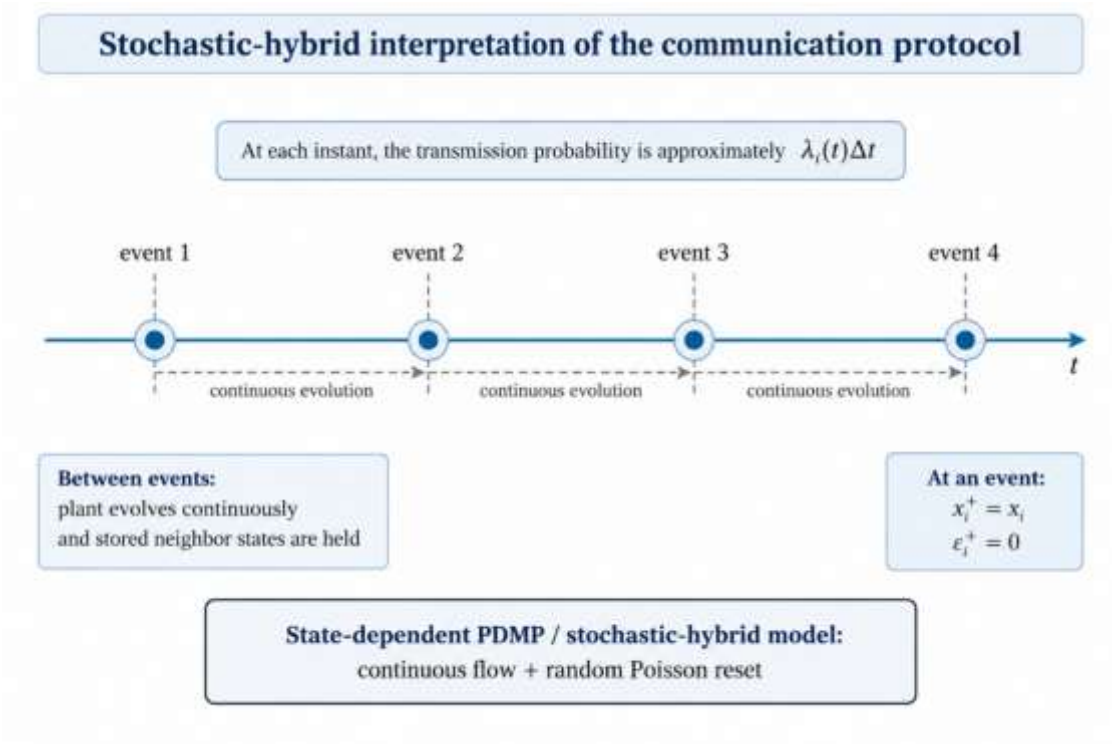


Figure 2. Stochastic-hybrid interpretation of the communication mechanism.

Essentially, the following is simply illustrated in Fig. 2. Between communication instants, physical states change continuously. When an instant of communication is randomly chosen, it is used to unfreeze a state that had been frozen before as the one being transmitted. One can easily conceive this to be interpreted as a piecewise-deterministic Markov process, where deterministic flow is interrupted by jumps of stochastic nature. This is a much more natural interpretation than interpreting the Poisson process as a perturbation which enters multiplicatively. Here, a communication event per se does not cause a jump in the physical state. Instead, it merely affects the information available to the controller.

The jump makes an update to the communication state, while the plant continues to evolve according to its physical dynamics.This distinction will become important for stability analysis, for a quadratic Lyapunov function can be evaluated both along the flow and at the communication reset. The diffusion part in the resulting infinitesimal generator consists of the usual derivative component associated with the plant dynamics, supplemented by a jump component scaled by the communication intensity. This precisely coincides with the structure used in stochastic hybrid or piecewise-deterministic systems.

3.4 Distributed controller and stability condition

For the numerical study, the distributed controller has the form

$$u_i = -Ke_i.$$

Assuming communication has a sufficiently high frequency, the neighbour states maintained by the friend states converge toward the neighbour states. Then the controller converges toward the usual smooth consensus controller. When the communication is perfect, the disagreement modes are governed bymatrices of the form $A - \lambda_r BK$, where $\lambda_r$denotes a nonzero Laplacian eigenvalue. Thus, network connectivity and controller design remain directly coupled.

For a connected undirected graph, the consensus subspace corresponds to the zero eigenvalue of the Laplacian. The remaining eigenvalues determine the evolution of the disagreement modes. This spectral interpretation has been a defining aspect of the graph-theoretic perspective on multi-agent systems since the first pioneering papers on consensus and formation control.The controller can be designed through standard Lyapunov inequalities or linear matrix inequalities. If $P > 0$is a quadratic Lyapunov matrix, a nominal disagreement mode satisfies a condition of the form

$$(A - \lambda_r BK)^T P + P(A - \lambda_r BK) < 0.$$

By means of an equivalent standard change of variables, the controller design can be further reduced to the form of an LMI. On the computational side, this is an advantage since LMI's have tractable solution procedures and are able to incorporate multiple robustness constraints simultaneously. In the present work, the stability analysis is primarily used to guide the structure of the technique and should not be interpreted as a definitive and comprehensive stability theorem for every possible stochastic communication mechanism. Of particular interest here is that the state-dependent intensity couples the communication process to the state of the system. A definitive theorem in the general case would require a positivity analysis of the jump contribution to the Lyapunov generator. This is a technical challenge and is considered a limitation of this work.

3.5 Communication cost

A useful feature of the proposed approach is that communication effort has a direct mathematical interpretation. If $N_i(T)$is the number of transmissions generated by agent $i$over a horizon T, then

$$E[N_i(T)] = E\int_0^T \lambda_i\,(t)\,dt.$$

Consequently, the total expected communication cost is the sum of these integrals. Due to the bounded adaptive intensity, the expected number of transmissions is bounded on each finite horizon. This yields the performance criterion that may include consensus error, energy of the control, and cost of communication. The goal is not to minimize the Poisson intensity as much as possible; the goal is to attain the lowest communication intensity satisfying a desired level of consensus performance.

4. Numerical Study

4.1 Experimental setup

The first numerical experiment considers five single-integrator agents,

$$\dot{x}_i = u_i,$$

connected through the path topology $1-2-3-4-5$. The initial states are selected as $x(0) = [0, 1, 2, 3, 4]^T$, creating a clear initial disagreement. The controller gain is $k = 1.5$, The horizon is 20 seconds, and the numerical integration interval is 0.005 seconds.

The Laplacian eigenvalues of the five-agent path graph are

$$0,\ 0.38197,\ 1.38197,\ 2.61803,\ 3.61803.$$

Thus, the graph is connected, and its algebraic connectivity is 0.38197. This provides a useful baseline because the convergence of a consensus protocol is strongly influenced by the nonzero Laplacian spectrum.

There are three different implementations. The first one (continuous) is the gold standard optimal bounds on the communication cost. The second (fixed) implementation takes the Poisson transmission intensity constant at 2.5. The third implementation uses state-dependent adaptive Poisson transmission. Sixty Monte-Carlo trials were run for each stochastic comparison. The key quantities of interest include the integrated squared disagreement, control energy, number of transmission events, and the disagreement at the end of the experiment. To make the time-integrated average consensus error simple, it is defined as the integral over time of the mean squared deviation from the instantaneous group average. It incentivizes fast convergence to consensus and discourages persistent disagreement; it is computed as a simple numerical integral of the squared disagreement. The number of transmission events is conveniently tallied and allows the control performance and communication cost to be compared in the same experiment.

4.2 Communication-intensity sweep

The most informative experiment varies the minimum Poisson intensity. The results are shown below.

Table 1. Effect of Minimum Poisson Intensity on Communication Frequency and Consensus Performance

Minimum intensity	Integrated consensus error	Mean communication events	Final disagreement
0.2	4.9418	36.9	0.0504
0.5	3.3019	68.7	0.003

0.75	3.1873	89.3	0.0008
1	2.6991	119.5	0.0002
1.5	2.4826	164.8	≈0
2	2.3759	213.9	≈0
3	2.169	313	≈0

The numerical trend is clear. Increasing the minimum intensity increases communication, but it also improves consensus. At the lowest tested value, $\lambda_{\min} = 0.2$, the system uses only about 37 communication events but retains a final disagreement of approximately 0.05. Increasing the minimum intensity to 0.75 reduces the final disagreement to approximately 8×10^{-4}, while approximately 89 communication events are required. At $\lambda_{\min} = 1$, the final disagreement falls to approximately 2×10^{-4}, with approximately 120 communication events.The relationship between minimum intensity and communication events is shown in Figure 3.

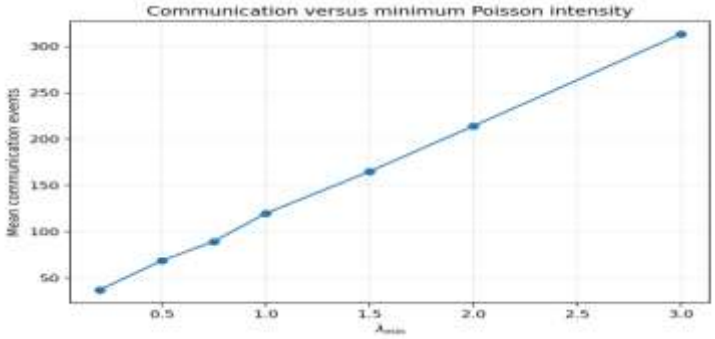


Figure 3. Mean communication events as a function of the minimum Poisson intensity.

The corresponding consensus-performance trend is shown in Figure 4.

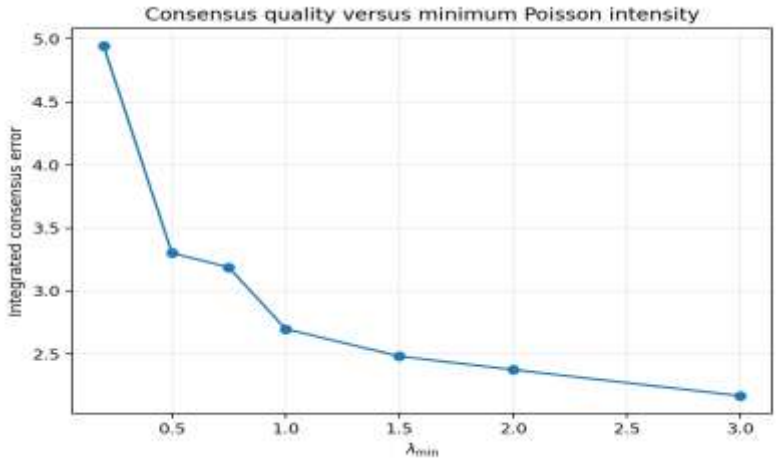


Figure 4. Integrated consensus error as a function of the minimum Poisson intensity.

Among all the numerical results of this paper, these two might be the most important. They establish that one cannot address the reduction of communication independently of the reduction in consensus. For too small an intensity, the neighbour information stored will become stale, and the controller will operate with stale information. As the intensity increases, the stored information remains more recent, and the level of disagreement drops.

A particularly useful operating point occurs around $\lambda_{\min} = 1$. Compared with the fixed Poisson experiment, which generated approximately 245 communication events, the adaptive strategy required approximately 120 events while producing a final disagreement of approximately 2×10^{-4}. This corresponds to roughly a 51% reduction in communication events. The integrated consensus error was approximately 2.70 for the adaptive strategy, compared with approximately 2.57 for the fixed Poisson strategy. The difference is relatively small compared with the reduction in communication.

Once the amount of communication is taken into account. This observation should be taken with a grain of salt. The adaptive method is not always better than fixed Poisson communication on a case-by-case basis, and the benefit of the adaptive communication is that it adjusts the amount of communication to the current state. It is very natural to have increased intensity at large discrepancies and reduced intensity at consensus, as the philosophy of event-based communication is precisely to avoid communications that do little or no additional control improvement.

4.3 Robustness to uncertainty

A subsequent experiment incorporates multiplicative uncertainty within the input channel. Numerically, the model is expressed as

$$\dot{x}_i = (1 + \delta_i)u_i,$$

where the uncertainty satisfies $| \delta_i | \leq \bar{\delta}$. The uncertainty bound is varied from zero to 0.4.The adaptive strategy continues to produce small final disagreement over this range. Its integrated consensus error varies from approximately 2.65 to 2.77, while communication remains close to 115–122 events. The fixed Poisson strategy maintains a lower integrated error, but requires approximately 245–251 communication events.The comparison is shown in Figure 5.

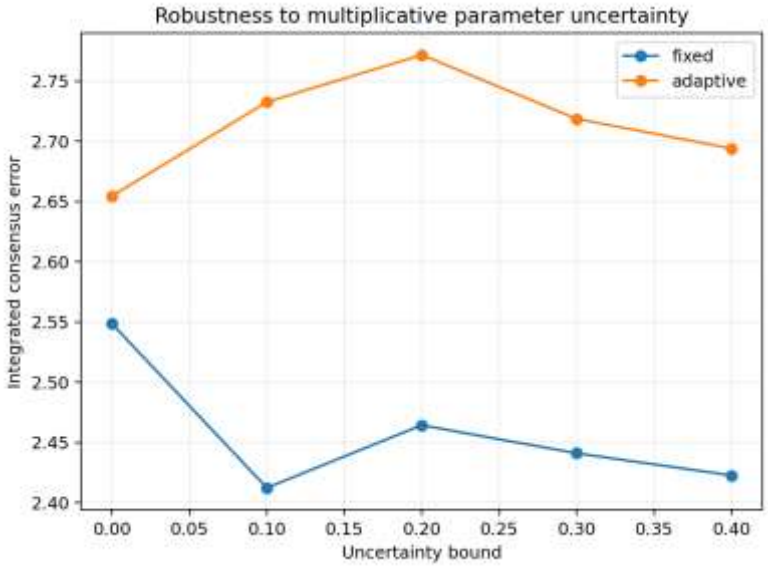


Figure 5. Consensus performance under multiplicative uncertainty.

So this is a positive result, but it should be taken with some caution. It shows that this proposed means of communication can still work with a higher amount of uncertainty, but it does not prove that adaptive Poisson communication is stronger than a fixed one. In this experiment, the fixed approach actually has less integrated error. The main advantage, still, for the adaptive approach appears to be reduced communication.This distinction is highly relevant for reproducibility of research. Adaptive controls are often justified as better simply because they occur less often; however, less often is only advantageous if the resulting quality of control is still acceptable. As a result, this experiment treats the number of communications and consensus error as separate measures of performance, rather than combining them into a single total that could mask a trade-off.

4.4 Scalability

The final numerical experiment examines networks with 5, 10, and 20 agents under 20% multiplicative uncertainty. The communication results are shown in Figure 6.

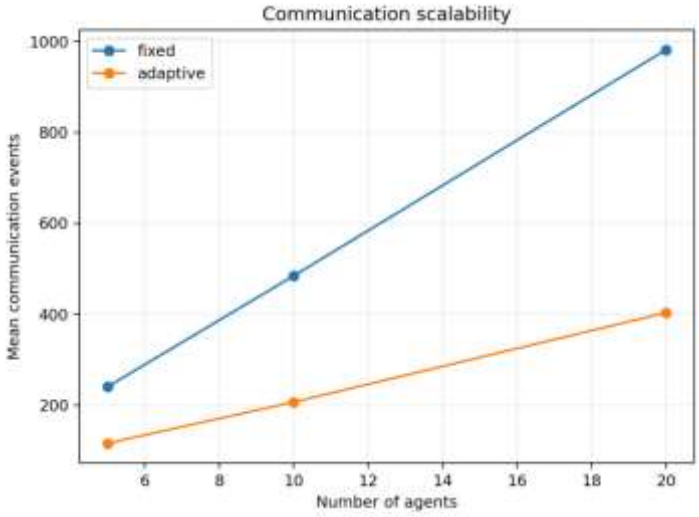


Figure 6. Communication events as the number of agents increases.

For five agents, fixed Poisson communication generated approximately 241 events, while the adaptive strategy generated approximately 116 events. For ten agents, the corresponding values were approximately 484 and 207. For twenty agents, fixed Poisson communication generated approximately 981 events, compared with approximately 404 for the adaptive strategy.As a result, the adaptive approach resulted in reductions in communication by about 52%, 57%, and 59% over the three network sizes. This provides the most significant quantitative evidence that a state-dependent communication policy may become more lucrative as the communication requirement (and the network size) increases. However, the larger networks also exhibit a drawback - as the size of the network expands, the integrated consensus error alsoincreases.What can be seen in the twenty-agent network is that the adaptive approach results in a final disagreement of about 0.93, in comparison to a final disagreement of about 0.69 for fixed Poisson communication. Therefore, for larger path networks, the simple controller that this numerical study employs does not provide performance of sufficient robustness.

This result should be hardly unexpected. As the number of agents increases, a path graph becomes weakly connected and algebraic connectivity decreases. No network topology is weak enough to be completely compensated by the communication protocol. The importance of network connectivity and spectral properties of the Laplacian is already well known in the classical graph-based consensus literature.Consequently, this test of scalability provides a convenient starting point for further development of the method. Instead of keeping the gain of the controller fixed for all network sizes, it should be designed according to the actual spectrum of the network. The LMI-based controller can include the smallest and the largest nonzero Laplacian eigenvalues and be recomputed when the network is topologically changed.

5. Discussion

The numerical experiments suggest a relatively straightforward interpretation of the method: communication acts as a control resource. Without signalling, consensus is achieved most efficiently but at a high cost, while waiting too long for signalling causes controllers to communicate with out-of-date neighbour states, slowing down convergence. By adjusting the transmission probability according to the level of disagreement, the adaptive Poisson serves as a compromise between these two extremes. A practical analogy is that of mobile robots in formation, where positions are changing quickly; regular broadcast updates prevent the build-up of out-of-date information, while once stability is achieved, continual broadcast offers little additional benefit; an intensity dependent on the state balances network responsiveness with the potential for inconsistent communication patterns over the mission.

Far from employing deterministic event-triggered schemes in which communication is forced once the error exceeds a threshold, the Poisson provides a probability of transmitting, and such randomness can smooth out the network traffic when many nodes trigger simultaneously, although a full analysis of collisions and dropped packets must be performed before any such advantage can be realized in real network environments. The design fits naturally into communication-control co-design. In wireless control systems, where a great deal of design flexibility is available in the communication protocol, decisions regarding communication have a direct impact on controllability and on closed-loop performance. In this context, the only design choice is the Poisson intensity, which bridges the control goals with the expected communication cost.

Several limitations still remain. First, the agents in this approach are single-integrator, as opposed to real robots with more advanced dynamics and nonlinearity. Second, the uncertainty can be modelled as multiplicative and very simplified; real robust control would require structured matrix uncertainty and LMIs. Third, the communication model assumes perfect transmissions, ignoring delay, interference and packet loss. Fourth, the stability analysis is still far from complete: because the intensity is state-dependent, a complete proof would require a stochastic-hybrid Lyapunov analysis; simply plugging in a minimal intensity into an LMI does not work unless the jump terms are allowed to admit such substitution.

Thus, this work should be viewed as an existence proof, and not a general theorem of stability. Still, from the experiment results, the proposed approach can cut in half the communication required in a five-agent setting while maintaining the potential for disagreement at an insignificant level. Larger networks amplify savings but reveal more consensus degradation.The most natural design parameter is $\lambda_m in$. Rather than arbitrary selection, applications could specify a maximum consensus error and choose the smallest $\lambda_m in$meeting that requirement. For the five-agent test, a tolerance of 10−3 suggests λ_min ≈ 0.75. This value depends on the controller, graph, uncertainty, and horizon, but illustrates systematic tuning.

The viewpoint would modify the problem to be an optimization problemnot just for the cheapest set of transmissions, but a compromise between communication and control quality. A more general statement might optimize both the expected communication and energy of control, subject to a fixed value of the disagreement, conforming with the more general view that communication, sensing, and actuation are coupled resources.

6. Conclusion

In this work, a communication methodology based on an adaptive Poisson process was investigated for the enablement of distributed consensus in uncertain multi-agent networked systems. The conceptual basis of the methodology consists of what was referred to as state-dependent communication. Agents communicate at a high rate when local divergence is significant, and the communication rate is smoothly reduced when concordance is gradually attained between them. The resulting system was modelled as a stochastic hybrid system, with the physical states evolving continuously and the stored communication states being randomly refreshed.

The numerical study provides evidence that this mechanism can reduce communication substantially while maintaining useful consensus performance. In the five-agent experiment, increasing the minimum intensity from 0.2 to 3.0 reduced integrated consensus error from 4.94 to 2.17, but increased communication from approximately 37 to 313 events. At a minimum intensity of one, the adaptive method required approximately 120 communications, compared with approximately 245 for the fixed-Poisson strategy, representing a reduction of about 51%. The corresponding final disagreement was approximately 2×10^{-4}.The experiments also highlight one important limitation. Reducing communication alone does not necessarily result in better control. At low communication levels, old information accounts for more differences. Furthermore, as the network grows, the simple controller used in the experiments will become less and less effective, particularly when dealing with path graphs with small algebraic connectivity. These results make the point that one has to think of communication and control as something to be designed together.Thus, the main conclusion of this paper does not appear to be that the Poisson communication outperforms a purely deterministic communication scheme or one which uses a fixed communication rate. In fact, what this paper demonstrates is that the intensity of communication can itself be treated as a measure of a manipulable, flexible resource. The next best step is to combine the adaptive Poisson law with the LMIs-based controller and prove the minimum intensity of communication for mean-square consensus with structured uncertainty. This would then allow the minimum rate of communication to be optimized subject to a given level of mean-square consensus accuracy. Such an extension would take the approach presented in this paper from a numerical 'proof of concept' into a technique for the co-design of control and communication.

References

1. Boyd, S., El Ghaoui, L., Feron, E., & Balakrishnan, V. (1994). *Linear matrix inequalities in system and control theory*. SIAM.

2. Davis, M. H. A. (1984). Piecewise-deterministic Markov processes: A general class of non-diffusion stochastic models. *Journal of the Royal Statistical Society: Series B (Methodological), 46*(3), 353–388. (OUP Academic)

3. Ding, L., Han, Q.-L., Ge, X., & Zhang, X.-M. (2018). An overview of recent advances in event-triggered consensus of multiagent systems. *IEEE Transactions on Cybernetics, 48*(4), 1110–1123. (PubMed)

4. Fax, J. A., & Murray, R. M. (2004). Information flow and cooperative control of vehicle formations. *IEEE Transactions on Automatic Control, 49*(9), 1465–1476. (IEEE Xplore)

5. Ghatak, G., Joseph, G., & Quan, C. (2025). Channel access strategies for control-communication co-designed networks. *IEEE Transactions on Control of Network Systems, 13*(1), 117–129. (TU Delft Research Portal)

6. Heemels, W. P. M. H., Donkers, M. C. F., & Teel, A. R. (2013). Periodic event-triggered control for linear systems. *IEEE Transactions on Automatic Control, 58*(4), 847–861. (Eindhoven University Research Portal)

7. Heemels, W. P. M. H., Johansson, K. H., & Tabuada, P. (2012). An introduction to event-triggered and self-triggered control. In *Proceedings of the 51st IEEE Conference on Decision and Control* (pp. 3270–3285). IEEE. (Eindhoven University Research Portal)

8. Jadbabaie, A., Lin, J., & Morse, A. S. (2003). Coordination of groups of mobile autonomous agents using nearest neighbor rules. *IEEE Transactions on Automatic Control, 48*(6), 988–1001. (SciSpace)

9. Lamperski, A., & Papachristodoulou, A. (2014). Stability and consensus for multi-agent systems with Poisson clock noise. In *Proceedings of the IEEE Conference on Decision and Control* (pp. 3023–3028). IEEE. (Experts@Minnesota)

10. Li, H., Zhong, M., Cao, J., & others. (2022). Event-triggered adaptive consensus for stochastic multi-agent systems with saturated input and partial state constraints. *Information Sciences, 603*, 16–41. (ScienceDirect)

11. Mesbahi, M., & Egerstedt, M. (2010). *Graph theoretic methods in multiagent networks*. Princeton University Press. (JSTOR)

12. Moreau, L. (2005). Stability of multiagent systems with time-dependent communication links. *IEEE Transactions on Automatic Control, 50*(2), 169–182. (Biblio)

13. Nedić, A., & Ozdaglar, A. (2009). Distributed subgradient methods for multi-agent optimization. *IEEE Transactions on Automatic Control, 54*(1), 48–61. (ResearchGate)

14. Nowzari, C., García, E., & Cortés, J. (2019). Event-triggered communication and control of networked systems for multi-agent consensus. *Automatica, 105*, 1–27. (ScienceDirect)

15. Olfati-Saber, R., Fax, J. A., & Murray, R. M. (2007). Consensus and cooperation in networked multi-agent systems. *Proceedings of the IEEE, 95*(1), 215–233. (Caltech CDS)

16. Ren, W., & Beard, R. W. (2008). *Distributed consensus in multi-vehicle cooperative control: Theory and applications*. Springer. (Springer)

17. Tabuada, P. (2007). Event-triggered real-time scheduling of stabilizing control tasks. *IEEE Transactions on Automatic Control, 52*(9), 1680–1685. (IEEE Xplore)

18. Wu, Y., Tang, N., Pan, X., Xu, M., & Liu, S. (2025). Adaptive sampling-based event-triggered consensus for multi-agent systems. *Systems & Control Letters*. (ScienceDirect)

19. Xie, D. (2016). Consensus for multi-agent systems with distributed adaptive control and an event-triggered communication strategy. *IET Control Theory & Applications*. (DOI)

20. Zhang, J., Ren, C.-E., & Fu, Q. (2021). Adaptive event-triggered control for stochastic nonlinear multi-agent systems with unknown control directions. *International Journal of Control, Automation and Systems, 19*, 2950–2958. (DOI)