

Reviewers' comments:

Reviewer #1 (Remarks to the Author):

see attached

Reviewer #2 (Remarks to the Author):

The paper by Li discusses different ways of estimating entropy production rates applied to a beads-springs model in a temperature gradient. The paper explores three different ways of determining entropy production rates: by taking spatial averages, temporal averages and the lower bound provided by the thermodynamic uncertainty relation. The estimators are tested in numerical simulations of the aforementioned spring model. As such this paper is mostly methodological and potentially applicable to available experimental data. However no such tested is made on real experimental data so it is hard to evaluate its impact. I have reservations this paper will attract the interest of a broad readership. The paper is rather technical and the conclusions not so exciting. To my regret I cannot recommend it for publication.

Reviewer #3 (Remarks to the Author):

In this paper, the authors demonstrate a protocol for measuring dissipation rates in nonequilibrium systems by considering the exactly solvable bead-spring-coupled-to-hot/cold-reservoirs model. Apart from the obvious spatial and temporal averaged entropy production rate, they also consider the less obvious lower bound of the entropy production rate given by the thermodynamic uncertainty relations. Using numerical simulations of the model they measure the entropy production rates using the three possibilities in the case of two bead and five bead systems and establish convergence properties of these estimates as function of driving rate and dimensionality. Further, they consider optimization of the weight function that enters the bound given by the thermodynamic uncertainty relation.

Pros for the paper: The paper is a carefully considered work of potentially great relevance to various nonequilibrium systems that are presently the topic of extensive investigations. For an expert theorist, it is a very well written exposition of the key ideas. I especially liked learning about the weak driving limit and the fact that as dimensions go up I am much better off using the TUR bound.

Cons for the paper: I do not think the paper is accessible to the wide audience that Nat. Comm has and in particular to the many of us lay people who are not steeped in stochastic thermodynamics but need to understand this stuff in order we be able to apply this to our systems.

I realize the technical nature of the work limits what can be done for the accessibility of the paper. But I have a few suggestions:

a) I really liked the clear story laid out that leads the reader to Eq.7. I would suggest that a similar narrative should be put in just above and just below Eq. 14 so that the TUR does not just pop out of nowhere for the reader. I did not understand what  $d(x)$  was till I went back and read some of the associated literature.

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In conclusion, this referee really likes the paper and thinks it should be published following some revisions from the authors to enhance accessibility to non-experts.

Dear Dr. Dubrovina and Reviewers:

Here are point by point responses to the reviews.

Regards,

Junang Li, Jordan M. Horowitz, Nikta Fakhri, and Todd R. Gingrich

**Review 1:** Entropy production is a hallmark of non-equilibrium processes. How to determine it from experimental data is a major challenge especially when not all relevant degrees of freedom are accessible. Recently, a new theoretical tool, the thermodynamic uncertainty relation (TUR) has been found. It allows to infer a lower bound on entropy production from mean and variance of any (even a coarse-grained) current. The present authors discuss estimators based on different choices of the current in a case study for an analytically solvable model with two degrees of freedom. They also compare the estimate based on the TUR with a direct evaluation taking into account spatial and temporal coarse-graining. In general, I would not consider such a, in principle rather simple, case study as appropriate for a high profile journal. However, since the TUR has generated enormous interest in the community, a critical assessment on its practical implementation as done here may indeed find a broader audience and thus may have significant impact.

We agree that the model is simple and that the analysis rises to the level of this journal due to intense recent interest in making use of the TUR. We think a critical evaluation of simple models is particularly impactful when it can inform such experimental applications.

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high-dimensional grid, where it is well known that Monte Carlo integration becomes a superior method.

The temporal integral can be thought of as a convenient way to implement such a Monte Carlo integration, with sampled  $\mathbf{x}$ 's coming from the configurations of the stochastic trajectory. Notably, Eq. (13) is computed from estimates of the thermodynamic force near the sampled configurations  $\mathbf{x}_{i\Delta t}$ , precisely where the finite trajectory has most reliably sampled. In contrast, Eq. (12) requires spurious extrapolation of the kernel density estimates ( $\hat{\rho}$  and  $\hat{\mathbf{j}}$ ) to points which are far from the any sampled configurations. The advantage of the temporal estimator over the spatial one becomes even more pronounced as dimensionality increases. Nevertheless, even  $\hat{S}_{ss}^{\text{temp}}$  becomes harder to estimate when  $\mathbf{x}$  grows in dimensionality. Getting accurate estimates of  $\mathbf{F}$  around the  $\mathbf{x}_{i\Delta t}$  requires observing several trajectories which have cut through that part of configuration space while traveling in each direction. But when the dimensionality is large, recurrence to the same configuration-space neighborhood takes a long time. Consequently, we turn to a complementary method which can be informative even when  $\mathbf{x}$  is too high-dimensional to accurately estimate  $\mathbf{F}$ ."

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We agree that if one has access to the thermodynamic force the thing to do is to estimate dissipation using the temporal estimator. Given the force, there is no reason to appeal to the TUR when the actual dissipation rate (as opposed to a bound) can be found directly. Our focus in this manuscript is the scenario in which one cannot get a clear picture of the thermodynamic force because the phase space is too vast. Then one could try to use the TUR to get a bound, making it important to understand how tight that bound will be. The tightness, however, is strongly influenced by which scalar macroscopic current is chosen (the choice of  $\mathbf{d}$ ).

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3a. One striking example that shows the power of the TUR to bound the efficiency of molecular motors is given by Seifert in *Physica A*, 504, 176, 2018, where extant experimental data on kinesin are analyzed.

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We appreciate this reviewer's positive feedback. We're glad that the work was generally received as well-written and we've sought to make the technical part of this work more accessible to an audience that does not entirely consist of expert theorists.

Cons for the paper: I do not think the paper is accessible to the wide audience that Nat. Comm has and in particular to the many of us lay people who are not steeped in stochastic thermodynamics but need to understand this stuff in order we be able to apply this to our systems. I realize the technical nature of the work limits what can be done for the accessibility of the paper. But I have a few suggestions: a) I really liked the clear story laid out that leads the reader to Eq. 7. I would suggest that a similar narrative should be put in just above and just below Eq. 14 so that the TUR does not just pop out of nowhere for the reader. I did not understand what  $d(x)$  was till I went back and read some of the associated literature.

b) Expand the figure captions to hold the hand of the reader more. For example Fig 3 a. Adding one more sentence or a phrase to help the reader keep track of the fact that entropy production is a  $j \cdot d$  thing and hence the statement of accumulation of current implies higher entropy production and therefore a farther from equilibrium conclusion. An inset in fig 3a that zooms in to show what  $j \cdot d$  looks like. I am just giving some example here. The authors are best able to see what might help the reader follow along and realize the importance of what the authors are saying.

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Thank you! We'll be interested to learn if our rewritten sections have helped make the work more accessible.

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I have read the reply of the authors and the revised manuscript. I am fully satisfied with both  
  
and do recommend publication as now is.

Reviewer #2 (Remarks to the Author):

I have seen the response by the authors to my concerns. However I cannot see in which direction the new submitted manuscript has improved. In their response to my criticism the authors respectfully disagree with my report. At least I was expecting to see an implementation of the method to experimental data or, in their absence, to numerical data obtained from a realistic model. The authors have not even made the least effort to show me that I am wrong. I do not see what my contribution as reviewer can be at this stage. I can only keep my recommendation of rejecting the manuscript.

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The revised manuscript indeed is more accessible to stochastic thermo novices. I am happy to recommend publication.

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Throughout the second half of the paper we have made several changes to cut, rephrase, or relegate to a footnote some of the more notationally dense and technical sections. As the reviewer points out, this is intrinsically a technical piece of work, so only so much can be done. We feel that real improvements have been made, however to the readability.

In conclusion, this referee really likes the paper and thinks it should be published following some revisions from the authors to enhance accessibility to non-experts.

Thank you! We'll be interested to learn if our rewritten sections have helped make the work more accessible.