Social Thermodynamics: Modelling Communication Dynamics in Social Network

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ABSTRACT: *Thermodynamics, a concept thought of two centuries ago, refurbished and elaborated since, assimilated and transposed to distinctive disciplines stretching from neuroscience to economics but still lacks in-depth exploration of its impact on social networks. The aim is to model thermodynamic principles after social networks, to understand how different variables of the system such as entropy, temperature, energy and pressure steers the communication between agents at a broader sense. These innate synthetic variables of social thermodynamics can expose; varied and difficult to analyze dynamics in a network with higher order of approximation. Quantifying these variables in this context has promising applications in business intelligence, information diffusion and network analysis. This paper casts light on distinct attempts to measure social entropy and other social thermodynamic variables, while presenting methods to construct various thermodynamic processes to study these variables in a restricted environment. We further discuss our observations, findings and challenges in modeling social network as a thermal gaseous system. The paper focus on how these variables behave and what the standard relations signify in social context, more detailed analysis of Isochoric and Adiabatic process equivalents are studied while addressing roadblocks encountered by theorists in the past. Our models are experimented with sample sets collected over a period of 6 months from an enterprise social network for 250K users with over 860M connections. We aim to extend the scope of social interaction analysis beyond today's limitation, thus benefiting from many wide-established principles in thermodynamics.*

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1. Introduction

Resemblance between thermal gaseous system and social network is more than what meets the eye. The way agents interact with each other, exchange emotions and opinions affecting the way other agents steer constantly, suggests the existence of energy transfer in social system. Thus it is fair to think that social networks possess internal energy in some form and constantly try to reach equilibrium state. Rise in complexity, change in energy states provides something to start with at ground level, to work our way out towards social thermodynamics. Advantages of knowing social entropy, pressure and temperature are endless with respect to information diffusion and communication modeling. Despite being decade's old concept, very little work has been done in the direction of applying these principles to social thermodynamics. Interdisciplinary collaboration and lack of proper test bed are most cited issues. Social network modeled in this fashion can help us study behaviors, affinities betweenusers in terms of pressure and energy functions.

Despite the term '*social thermodynamics*' being used first in early 70's, lack of proper experimental platform to collect such context sensitive dynamic empirical data in good volumes hindered further research. Few scientists began to model social systems in the same decade from a far from equilibrium perspective. Ilya Prigogine, a Belgian chemist first explored non equilibrium thermodynamics in social context. [1] Georgi Gladyshev, a Russian physical chemist put forward the idea of hierarchical thermodynamics where social information networks could be studied by modeling systems with in systems approach by taking their internal energy and work functions into account. [3]

Dawn of online social networks sparked interest in the social thermodynamics field again, with easily available relevant data pools. Social systems fueled by rich interactions, in real time open doors for testing thermodynamic models for deep insights. [3] stated "*The value of ΔG ,Gibbs free energy corresponding to the formation of some human society, a complicated thermodynamic system, can be estimated by calculating the work that went into the building of the structure of that society*" [4] Modeling interactions in networks after thermal system hints promising impact on communication constructs and information behavior.

Communication is the primary means for information diffusion. Information causes change in social dynamics using people as a medium to move from one place to another. We tried to focus on how the synthetic thermodynamic variables relates, behaves and their significance in social context. Adiabatic and Isochoric process for social networks are modeled and studied while addressing roadblocks encountered by theorists in the past. This will extend the scope of social interaction analysis beyond today's limitation, benefiting from many well established thermodynamic principles. As an immediate result, we can estimate the ideal time to infuse information in a network, targeting very specific areas.

Modeling diffusion of information is a promising area in aiding us to understand the kernels of systems behavior, but proved to be tough to model the same for macrostates in social networks. Most of the current diffusion models in social networks highly depend on influence functions of individual users which is again a microstate property. [12] The innate dependence on network specific signals and attributes makes it more difficult to generalize these models to potential states. Ease of unambiguous separation of macrostates and availability of ample relations to judge system's perpetual synthetic properties with respect to other states, give social thermodynamics an unique advantage in understanding these core factors.

1.2 Criticism

Precision matters in science. It counts on measurable, objective, repeatable, observable evidences. However social science differs with this validation as most of the established research tends to identify phenomenons and general tendencies in the ways people interact. Very often this occurrence always tends to have outliers, hence not consistent like physical laws. This notion caused dismissal of theories contemplating about social thermodynamics. Paul Samuelson an economist criticized "*the sign of a half-baked speculator in the social sciences is his search for something in the social system that corresponds to the physicist's notion of entropy*" [5]

1.3 Structure of Flow

Talking about flow of the paper, barring the overview quoted in abstract section, Introduction reads in depth background of the problem space and benefits, roadblocks in solving it. Section 2 discusses more about social thermodynamics, barriers in literature work on social entropy and modeling diffusion in thermodynamics fashion. In addition to arguments on existence of thermodynamic models in social networks, criticism on molecular approach for the same casts light on divided opinions in the field. In the next section i.e., 3 we've talked about our approach to model thermodynamic processes in social networks and calculating various synthetic variables in conjunction with entropy. It continues to converse about feasibility of applying some established relations and needed assumptions to maintain the process state of the system. Continuing to 4th section i.e., observations/ discussions depicts sample data obtained from our analysis and a short note about probable inference from thermodynamic properties. Before citing the much helped references we d presented our conclusion in detail and further directions to extend the work.

2. Social Thermodynamics

Thermodynamics digs into the association between energy transformation with respect to dynamic variables like volume, evolution of efficiency, temperature, entropy, work and pressure. There are quite a number of similarities here with social networks adhering to certain properties of the system. When we start to think people as molecules in a gaseous state, molecules gain/exchange energy in the form of interactions which guide the flow of temperature in the system. It states that they possess potential energy as well. [7] People are in motion with change in network topologies, affinities between each other. First law states $\{Q = U + W\}$ when a fixed mass of gas is supplied with additional heat, it invariably gains internal energy and expands corresponding to the amount of work done thus conserving the energy. This phenomenon is evident in social groups where high energy in a pseudo macrostate affecting the entire system as an effect.

Definition of equilibrium is perpetual in social systems, as it allows a single molecule to be in different states of equilibrium with respect to the pseudo macro state in consideration. In an example between two agents M_A and M_B of a system, the definition of state of equilibrium varies from what they develop with external systems where both the agents are not mutual members. [15]

2.1 Macrostate Variables

We are trying to take a fresh look at social communication by observing microscopic properties and how they give rise to various macrostate phenomenons scientifically. In an real social thermal system, emotions carry the real energy. Social interactions generated by users act as carriers of these emotions. These interactions in turn mobilize through channel bridges, what to be otherwise called connections between users. In near real system, ability of an interaction to get transmitted across multiple channel bridges highly depends upon type and depth of the connection between hops. So to study such a complex evolving system, one has to make certain assumptions about energy absorbed by molecules in each cycle, [17] work done which affects the affinity, strength of channel bridge to establish and control certain thermal processes. Assumption is that in ideal social thermodynamic system molecules interact without any energy dissipation or absorption, external work done has negligible effect on affinity between people, all channel bridges are equi volume & all states are equi probable. With increase in the number of people, energy increases in the system as long as there are new interactions. Assumption is that all channel bridges are of the same volume and with the same ability to transfer information, where in reality with increase in affinity between agents increases the volume of pipe (i.e., probability of information passing from one end to end), lso that there is no energy loss/absorption by molecules to control the thermal state [11]. Thus ignoring strong ties vs weak ties classification as people alone doesn t matter without the bridge between them and any disconnected agents (molecules) doesn t affect the above system.

Complex social systems generally adhere to elementary factors like Homophily, Confounding, Induction and can be clearly split up across them. [7] An ideology or behavior is usually inducted from agent to agent, eventually leading to grouping similar people which is homophily. It helps us to identify and observe a pseudo macrostate with more clarity as the flocks tend to be easily predictable than individual microstates. [15] An ideology or behavior that spreads from user to user varies in pace and energy. Higher the energy difference faster it spreads. Thus it is fair to think that social networks possess internal energy in some form and constantly try to reach equilibrium state.[9] Change in energy states gives us something to work with, at ground level to work our way out to system thermodynamics.

In a closed gaseous system, temperature T and pressure P are proportional to each other. In a social system modeled after a gaseous state, people are swapped for molecules 'N' and connection pipes contribute for volume 'V' as they depict more accurate meaning of system boundaries.

2.2 Entropy

Interpretation of term '*entropy*' is quite ambiguous with respect to application context. It differs in meaning from thermodynamic to statistical mechanics and other areas. In essence it s a measure of randomness/ energy that s unavailable for work. Going by the laws, entropy of a closed/isolated system always tends to increase or remains same, while universe as a system is considered to have the maximum entropy of all. Clausius R. (1850) was the first person to quantify entropy of an isolated system. Due to shortcomings caused by excluding microscopic nature of system in his model, a new statistical definition was needed for deeper understanding of systems. Later by studying microscopic elements Boltzmann L. (1870) proposed that statistical entropy is similar to thermodynamic entropy and only differs by a constant multiplier (k = Boltzmann s constant) when taken into account. This approach drills down to entropy being proportional to log of no. of all possible microscopic configurations that can give rise to a referred macro state. Statistical definition $S = -k_B \ln \Omega$ says, it s a scale of uncertainty that reveals after eliminating all the observable macroscopic properties like Temperature 'T', Pressure 'P' and Volume 'V' [13]. Microstates reveal granular details about the system like change in internal energy and local influence. [8] Entropy in the system would increase with more such states being available in the system with high probability. [10] Entropy can be calculated for a set of these macroscopic variables by measuring the extent to which total degree of the probability of system is spread out into different possible microstates. Basic equation measures entropy as logarithmic density of all the possible (i) states, proportional to Boltzmann constant K_B. For Ω to be determined, all dynamic macroscopic variables should be included.

Most of the statistical thermodynamics work under an assumption that system is isolated and is in equilibrium, which makes occupation of all microstates equally probable.

$$P_i = 1 / \Omega$$

P_i is defined as probability of system being in i^{th} state.

$S = k_B \ln W$ For non-equilibrium systems, Ω (N, T, V, X..) is a function of complete set of macroscopic variables, that includes everything that may change in the system under experiment, without which one might observe decreasing entropy due to non-equilibrium states. This amazingly simple equation by Boltzmann proves that no. of degrees of freedom of a system is related to number of possible microstates.

Shannon Entropy in Information theory measures the uncertainty factor accompanied with a random variable. This version of entropy by Shannon quantifies expected value of information in units of bits. In other words it is an amount of information one is missing when one does not know the complete manifestation of the random variable. This coding theorem has wide applications in data encoding and compression. One can understand it better this way, Higher the entropy, lesser the compression ratio. Highly random text can't be compressed beyond a point as entropy increase. It shows that the average length of the shortest probable way to encode information in a given set can be found with entropy / Log (no. of symbols) in the target set.

$$H = -\sum_{i=1}^{n} p_i \ln (p_i)$$

2.3 Social Entropy and Energy Functions

Quantifying entropy for social systems should be done with care by mapping all the constituents to right variables. Definition of entropy largely depends on what we think it is with respect to the system. In a general closed gaseous system, temperature 'T' & pressure 'P' are proportional to each other. In a social system that is modeled after a gaseous state, number of people are swapped for molecules 'N' and connections which acts as expandable pipes contributes for volume 'V' as they depict more accurate meaning of system boundaries.

Clausius thought heat has fluid nature while Carnot thought of it as a conserved property that transfers between multiple systems. Joshua K. (2011) gave a good building block for social entropy. [6] Mainly the sensible expression to measure multiplicity a function of Ω helps in deriving social thermodynamic entropy. Clausius saw entropy as a fixed quantity that corresponds to heat and temperature $S = Q / T$

As molecular theory gained audience with kinetic energy of gases, definition has been reasserted that entropy can only be defined for systems in thermal equilibrium. As T remains constant, increment can be represented as

$$\delta S = \frac{\delta Q}{\delta T}$$

Shannon's coding theorem had managed to reduce entropy to no. of bits, to encode any data into H bits based on the approximations closely to a coding system to convert any type of information into just bits. As mentioned above already, entropy is what we define and perceive. So social thermodynamics need its own version of entropy, which depends totally on locally available variables. Starting with the statistical logarithmic equation for entropy in physics,

$$S = K_s \ln (\Omega (N, V, U))$$

$$\text{Where } K_s = \text{Boltzmann constant}$$

Ω is multiplicity, a function of all macroscopic variables that undergo change [14] during a process in social networks. Multiplicity Ω is defined as number of microstates associated with macrostate. N, V, U are different microstate parameters considered by Joshua for multiplicity equation.

$$\Omega(N,V,U) = \frac{(n(n-1)/2)!}{V!\,(N(N-1)/2)-V)!}\left[\frac{(U-1)\,!}{(U-\mathrm{V})\,!\,(V-1)\,!}\right]$$

The network we'd considered for study uses follow model to make connections. So $(n\,(n-1)\,/\,2)!$ will be just $(n\,(n-1))$

2.3.1 Energy function of U (internal energy)

Before going into the details: calculating the unknown variable '*U*', energy function is very important, where social coefficient λ varies according to the type of interaction. α, β *and* γ are social network dependent constant.

$$U = \sum \lambda_i N_i I_i$$

$$Where\ ,\ \lambda = \left\{\begin{array}{l} \alpha, I \in \text{ Initiated Interaction} \\ \beta, I \in \text{ Received Interaction} \\ \gamma, I \in \text{ Indirect Interaction} \end{array}\right\}$$

$$N = \textit{number of users in an interaction}$$

Once we know *S* and *U*, it is easy to define and contain environmental configuration of the system, to work out synthetic parameters.

3. Experimental Models

Carnot cycle is an established ideal thermodynamic process in which macrostate of the system goes through a cycle of phases. This cycle accurately mirrors the dynamics of social networks except the concept of heat sinks. So, we chose a thermal system profoundly used in automobiles '*Otto Cycle*' as the closest analogous process. It cycles through four phases. Adiabatic compression: Work done increases the temperature without dissipating heat; Isochoric heating: Heat supplied at constant pressure raises the temperature; Adiabatic cooling: drastic decrease in pressure results in heat loss; Isochoric cooling: sudden decrease in temperature at constant volume due to heat loss.

We modeled and mapped isochoric heating and adiabatic cooling as in '*otto-cycle*' to social system. Volume is considered as the total connections in the network; Energy is the measure of total interactions happening in the system; Entropy is number of possible states in which the users can exist and Work is effort done by force in changing the state of social system. We assume, the mass of each user is constant and is negligible. In reality, they gain energy from the interactions performed and the connections established in a network; which in turn acts as a significant influence measure.

Isochoric process can be observed in a closed group of users with established and stable connections assuming negligible change in connections. All the energy in the system is proportional to the interactions occurring in the system. Reversible adiabatic cooling was difficult to model as quantification of external system is not feasible in our model. So we modeled adiabatic free expansion of gas where users make connections in absence of any external pressure from the network. Being an irreversible process, it cannot be described using ideal gas equations, hindering the process of calculating derived thermodynamic variables.

3.1 Case1: Isochoric Heating

Isochoric heating of social system happens when systems reach a maturity of volume by forming enough connections, after which it just gets heated up by interactions happening due to various external influences

At this point, system adheres to the condition (*V is constant*, 'ΔV' = 0) making it feasible to calculate temporal pressure, Temperature, change in internal energy over time.

Ideal gas law equation says pressure '*P*' times volume '*V*' equals to no. of moles '*n*' times gas constant '*R*' and temperature '*T*'

$$PV = nRT$$

There is a problem with this useful relation. It s quite hard to rely on number of moles, an ambiguous undefined unit in social context, also the unknown gas constant which is not much of a use. Instead going by this other relation,

$$PV = N k_B T = nRT,$$

Universal Boltzmann constant is much better to rely on, while holding the same variables that we needed. Instead of moles we have N on the right side, which accounts for density of gas i.e., number of particles per volume. It corresponds to number of agents (molecules N) inside the macrostate.

As in Isochoric process, Volume becomes constant when system stops expanding after reaching the maturity level,

$$P \propto T \text{ ; } V \text{ is constant}$$

Also pressure and energy density aren t same but related. When you look at '$k_B T$', kinetic energy density of gas, it appears same at the first glance. When looked closely pressure is momentum flux applied in spatial direction while energy corresponds to temporal direction.

$$T = Q / S$$

Let's consider this second relation between temperature, heat and entropy. Thermal system in which entropy is an independent externally measured variable, temperature can be defined as derivative of the internal energy with respect to the entropy.

$$Q_{heat} = U_{Int' Energy} + W_{workdone}$$

While work done is 0, $\Delta V = 0$

$$T = \frac{dU}{dS}$$

Heat $\Delta Q = \Delta U$ (change in internal energy as new interactions get created and information flows)

$$\Delta Q = \sum \lambda_i N_i I_i$$

λi – Social coefficient
Every interaction doesn't carry equal energy and varies on interaction type. We call this a social network dependent variable. | Social coefficient

Ni = no. of people involved in an interaction (depends on type of interaction, group message, share, comment or whatever)
Vy - subjective volume based on my connections
Iz - change in interactions

$$S = K_s \ln (\Omega (N, V, U))$$

The macroscopic variables that are chosen for this function set $\Omega (N,V , U, X..)$ should comprise everything that may alter during the experiment. This is important as otherwise, one might observe decline in entropy which is again paradox to the property of entropy.

Any new information that s being infused into the system is some sort of interaction between agents. We think these interactions are responsible for energy addition into the system. Similar to photons they ve negligible mass but are responsible for energizing the system in every possible way, thus affecting the communication dynamics.

People are molecules who emit energy in terms of interactions, whereas connections between them are similar to pipes which constitute for actual volume. With increase in people, energy increases. Assumption is that all pipes are of the same volume with equal ability to transfer information, where in reality, with increase in affinity between agents increases the volume of pipe (i.e., probability of information passing from one end to end)] Ideally strong ties and weak ties should be factored in future models, as people alone don t matter without the bridge between them, In other words an isolated molecule cannot affect the system in any way.

In ideal scenario, molecules gain energy from the heat generated in the system. Some form of potential energy which affects the social affinities between connected molecules and in turn diffusion of data exists. This is an interesting direction to explore by quantifying these general properties.

$$Work = pdV \text{ (work done = 0 in this case)}$$

3.2 Case 2: Adiabatic Cooling

Adiabatic thermodynamic process does not allow heat transfer between system and surrounding. It s mostly an abrupt event, with not enough time to facilitate heat exchange. Free expansion is a process of expansion in vacuum, which in social system corresponds to people making connections in absence of external pressure.

It can be triggered with the arrival of an influential user, creating a huge impulse in the network. Despite arrival of an external user, network is still considered close because of negligible impact on number of users, when the number is high. Impulse generated sets the system in state of abrupt expansion in the absence of external pressure. Change in internal energy is ignored as there is probability of new interactions in this short-span of time is negligible.

$$\Delta H = \Delta U + \Delta W$$

$$\Delta H = \Delta W \; \{as\ \Delta U = 0\}$$

The entire process is irreversible, as the system goes into free expansion there is abrupt variation in pressure across the system with sudden dip in entropy and volume. So, the quantification of derived macrostate variables is infeasible.

4. Observations and Discussions

We think the unique advantage of observing an evolving network would lead to many interesting observations that are difficult to study with much established networks like twitter, without accurately predicting the macroscopic evolution in advance. Meaning, unless one has a holistic view of the entire system, it is quite hard to pinpoint the exact macrostate that might adhere to the conditions we intend to observe.

The above model has been tested on Knome, an internal social network in TCS connecting 250K users. It works on a follow model for building connections, an apt test bed for our proposed model. It is still an emerging network with about 877 Million recognized connections since its inception 6 months ago. To simulate the appropriate environment for the experiments, we selected mature connections that undergo minimal changes and ignored the budding connection networks. These set of connections and connected users represent a macro state. For these macro states the volume (V) remains constant as there is no new connections being developed and it can be considered as an isochoric socio-thermodynamic process.

We started by secluding the network from the other interfering data. We quantified the energy of the closed macro state using the amount of interactions observed using the equation 1. The entropy is calculated using equation 2 as a measure of all possible micro states possible. Using these values we calculated the temperature and pressure of selected macro state by comparing the change in energy and entropy over time.

Energy	Entropy
2092.6	1621.2075
2374.6	1731.60254
2631.8	1819.21564
2721.8	1847.52559
2971.6	1920.75794
3037.4	1938.9053
3129.8	1963.45951
3203.2	1982.61775
3340.2	2016.79129
3408.6	2033.16812

Change in Entropy
110.395
87.6131
28.30994
73.23236
18.14735
24.55422
19.15823
34.17354
16.37683

Various thermodynamic variables in action across time

Table 1. a) Isochoric Heating

Change in Entropy	Change in Entropy	Temperature	Pressure
110.395	282	2.554463	74.07943
87.6131	257.2	2.935634	85.13339
28.30994	90	3.179095	92.19376
73.23236	249.8	3.41106	98.92074
18.14735	65.8	3.625873	105.1503
24.55422	92.4	3.763101	109.1299
19.15823	73.4	3.831251	111.1063
34.17354	137	4.008949	116.2595
16.37683	68.4	4.176632	121.1223

Change in temperature corresponding to pressure when pegged to entropy at zild.

Table 1. b) Isochoric Heating

Table 1 lists the data from one such macro-state with 723 connections gathered over a month's period from interactions generated within these connections. They exhibit approximate linear increments in temperature and pressure with corresponding increase in energy which is plotted in Graph 1. We further divided this graph into 4 scenarios and compared those with the live data.

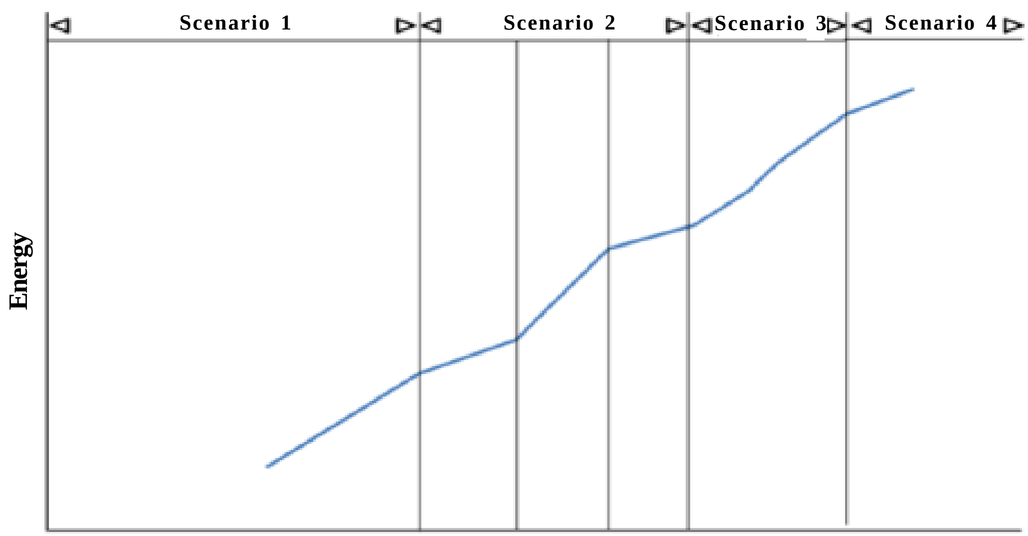

Figure 1. Graph T vs P across multiple scenarios

Scenario 1, 3 and 4 are the usual behavior of most of macro-states, with the significant increment in pressure with the increase in energy of the system. Interestingly the first and third half shows drastic pressure increments with less than average increase in energy and the second half show the lower increments for higher energy values. This behavior when referenced with the live data shows that the scenario 2 is a period of extended weekend with low participation in the network. The first half starts along with a major influential user initiating interaction causing a sudden surge in pressure value which attains equilibrium and second half has most of the interactions derived from this parent interaction and doesn't have any visible impact in pressure. The third part of the scenario marks the release of new features of the platform, exhibiting the effect of external pressure on the macro-state.

In our initial assumption we assumed that users in the macro-state have no mass. The first phase of scenario 2 exhibits the impact of mass of the user in the system as interactions generated by heavy users exert more pressure. The model does show the relevant dips and highs based on the mass but will need a major remodeling to consider masses for defining other major equations. We also assumed that there is a constant external pressure for the macro-state at any given time, but as evident from the phase 3 of scenario 2 the external force to affect the pressure in the macro-state and the algorithm needs to be tweaked for measuring and quantifying these impacts.

While modeling the socio-thermodynamic model and referencing it with live-data, we made few interesting observations as listed below:

Observation 1: The model assumes that there is negligible resistance to the information flow and every user acts as a perfect information dissipation in macro-state. The information diffusion though is highly dependent on the number of connections; increase in connections impacts the interaction patterns. So with increase in volume in the system, accession of information diffusion becomes more apparent. This may be defined as lowering of diffusion threshold with increase in connections, which in social networks means more interest groups to share information by lowering resistance for information flow. The diffusion threshold is defined as the ratio of heat generated to the heat absorbed for a user. In other words, it's a ratio of interactions generated to interaction. It is also observed that Influencers have a very low value for diffusion threshold, proving its inversely proportional to the mass of the user.

Observation 2: Under the constraint of constant heat, introduction of a probable high mass, influential and frequent user, referred as influential will have an explosive effect in social thermodynamics. Assuming the small time interval after the influential joins, the macrostate acquires new connections in this very short span. As the interaction remains constant during this period, there is a rapid drop in entropy of the macrostate since the possible microstates system can be with the now reduced energy drops significantly.

Increase in Volume	Change in entrophy
2	23.5
3	32
1	10
3	28.4
5	42
2	15

Table 3. Entropy change with the change in volume

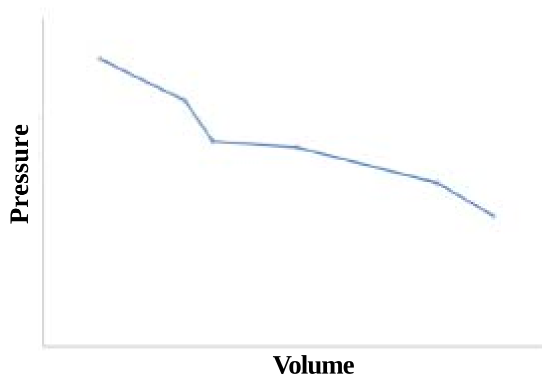

Figure 2. Change in P of the macrostate vs V

The arrival of influential user [2] exerts an imploding force on other users, leading to a rapid expansion in connections. This sudden surge in connection reduces the overall pressure of the macrostate, stabilizing the system and marking a new equilibrium. This is a hyper-expansion period for the macro-state in social network, new connections are made at a very high speed and there isn't enough data to keep the pressure and temperature constant at this stage causing a sudden drop in the temperature and overall pressure in the system. This scenario models the adiabatic expansion for socio-thermodynamic process.

Figure 2 shows the change in pressure of the macrostate with change in volume and Table 3 compares the entropy change with the change in volume.

This doesn't infer that the interactions have gone down, this just means that the average interaction per connection has reduced for the considered time. So the low temperature and pressure is not due to lack of enough interaction but due to decrease in overall entropy of the system.

5. Conclusiom

After analyzing and inferring from the recent work that has been done in the field of socio-thermodynamics, we mapped and modeled the same on an established enterprise social platform. We started with defining apparent thermodynamics variables in social context and used them to derive other dependent variables. We realized the simulation of isochoric process, selecting a group with matured, stable and non-changing connections to derive temperature and pressure. The impact of these variables on interaction patterns, information diffusion and influence analysis in social network are then observed and analyzed. We also modeled the impact of external impulse in the social system parallelly observing and analyzing it with real-data. We later discussed about the possible exploration areas to quantify individual influence and map diffusion patterns in social network. We concluded the paper with the discussions of scenarios the current model flounders and the possible recommendations for future research.

References

[1] Lipkowski, Mil. (1979). The Social Thermodynamics of Ilya Prigogine. Chemical and Engineering News, April 16.

[2] Ghosh, Rumi, Kristina Lerman. (2010) Predicting influential users in online social networks. arXiv preprint arXiv:1005.4882.

[3] Gladyshev, Georgi, P. (1997). Thermodynamic Theory of the Evolution of Living Beings. Commack, New York: Nova Science Publishers.

[4] Georgi Gladyshev. (1997). Thermodynamic theory of living things.

[5] Samuelson, D., Paul. (1972). The Collected Scientific Papers (p. 450). 3, ed. R. Merton. Cambridge, Mass.: MIT Press.

[6] Joshua, K, Anthony, N. Non-probabilistic Entropy of a Social Network, *Journal of Mathematical Sociology*

[7] Thermodynamics of Social Networks, http://www.scribd.com/doc/55368228/Thermodynamics-of-Social-Networks

[8] Gourevitch, B., Eggermont, J. J. (2007). Evaluating information transfer between auditory cortical neurons. *J Neurophysiol*, 97 (3) 2533–43.

[9] Konstantin, K., Victor, M., Raul, T., Maxi San, M. (2008). Nonequilibrium transitions in complex networks: a model of social interaction, Feb, PACS numbers: 87.23.Ge, 05.50

[10] Thompson, T. (2002). Definitions of entropy. http://www.tim-thompson.com/entropy1.html.

[11] Greg,V., Aram, G. (2012). *Information Transfer in Social Media*, WWW 2012 – Session: Information Diffusion in Social Networks Lyon, France

[12] Jaewon, Y., Jure, L. Modelling information difussion in Implicit Networks, http://cs.stanford.edu/people/jure/pubs/lim-icdm10.pdf

[13] Lionell, B., Anil, K., Adam, B. Granger causality and transfer entropy are equivalent for Gaussian variables, Centre for Computational Neuroscience and Robotics, http://arxiv.org/abs/0910.4514v2

[14] Maytham, S., Khaled, M., Ibrahim, S. (2008). Maximum entropy of a fully connected social network, *IADIS International Conference on Web Based Communities*.

[15] Aral, S., Muchnik, L., Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *PNAS*, 106 (51) 21544+, December.

[16] Human Thermodynamics Project, http://eoht.info

[17] Huankai, P., Ying, Z., Tad, H. (2012). Thermodynamic Principles in Social Collaborations, http://arxiv.org/pdf/1204.3663v1.pdf *In*: Proceeding CI 2012.