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Network Particle Tracking (NPT) and Post Path Analysis for Understanding Student Learning and Retention

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Network Particle Tracking (NPT) and Post Path Analysis for Understanding Student Learning and Retention

E. W. Tollner, Caner Kazanci and Qianqian Ma

Abstract

Network Particle tracking (NPT), followed by a post path analysis can provide an analysis for a non-conservative information flows based on preliminary results. In theory, one can model a curriculum with data on documentation and retention of instruction at the course. An analogue of thermodynamic temperature appears to measure the importance of the respective course compartments. These correlate roughly to the numbers of connections associated with various course compartments. The temperature values seemed not to be overly sensitive to the beta values used. We present an intense strategy to develop documentation needed to model a given curriculum. The time-honored concept of cycling in a curriculum, of conceptual revisits, stands validated by the analysis. The Finn Cycling index describes cycling system wide. The indirect/direct effects ratio describes how compartments other than adjacent compartments can affect results. The process can provide some objective measures, but the data acquisition would be intense both for students and for faculty. It is likely that specifically focused data gathering would provide almost as much insight as would an exhaustive NPT and post path analysis. The analysis suggests that good students can learn in any curriculum. What is not yet clear is the ability of various curricula to retain students.

Key Words: stochastic differential equation, network environ analysis, input-output models, compartment modeling, network particle tracking, ecological network.

Background

Engineering education is facing the need to increase the number of graduating engineers. To this end, several innovative educational approaches such as those of Gattie et al [9] and Kellam et al [18] propose design studio approaches. They are making efforts to describe and understand the education process as a system. In this paper, we extend work first presented in 2009 on a concept we called ‘Network Particle Tracking’, or NPT. After a brief recap of what particle tracking is, we extend the concept from ecological systems to one of a more general social system where, instead of modeling parcels of conserved substances such as energy as energy or mass moves through an ecological system, we extend to non-conserved information content. The NPT approach followed by a post pathway analysis moves towards an objective measure of effectiveness. The post pathway analysis refers to a detailed study of particle attributes based on relationships between time and particular paths through the network taken by individual particles.

Patten and colleagues developed network environ analysis (NEA) [3, 5, 7, 19, 20], a form of Ecological Network Analysis (ENA), to model the networks of complex ecological systems. Affording particular mathematical and ecological interpretive advantages, NEA uniquely represents objects as simultaneously participating in the dual environments of both their incoming and outgoing networks. NEA reflects the organic holism of ecological systems and is by nature deterministic.

Recently, Jørgensen and Nielsen [14], Fath et al [6], Jørgensen and Fath [16], Tollner et al [22] and Tollner et al [21] proposed various thermodynamic goal functions to describe developmental trends of ecosystems.

Tollner and Kazanci [22] presented a network modeling algorithm known as “Network Particle Tracking (NPT)” based on considerations from information theory, from the stochastic simulation of chemical reactions, and from statistical thermodynamics. NPT is an extension of network environ analysis (NEA) first proposed by Patten [19]. NPT models ecological systems by maintaining the system perspective yet providing a method for visualizing real time change within compartments. NPT discretizes mass or energy flows and storages in ecological networks into a series of ‘particles’ or ‘quanta’ of an identified mass or energy constituent (we will use 'particle’ from this point forward). Using a compartment network model as depicted in Figure 1, NPT documents the pathway of each particle from input through the system to output. An improved version of Gillespie’s algorithm [10] for solving stochastic differential equations extended the tracking capability of the Tollner and Kazanci [22] approach enabling feasible solutions to ecological-scale problems.

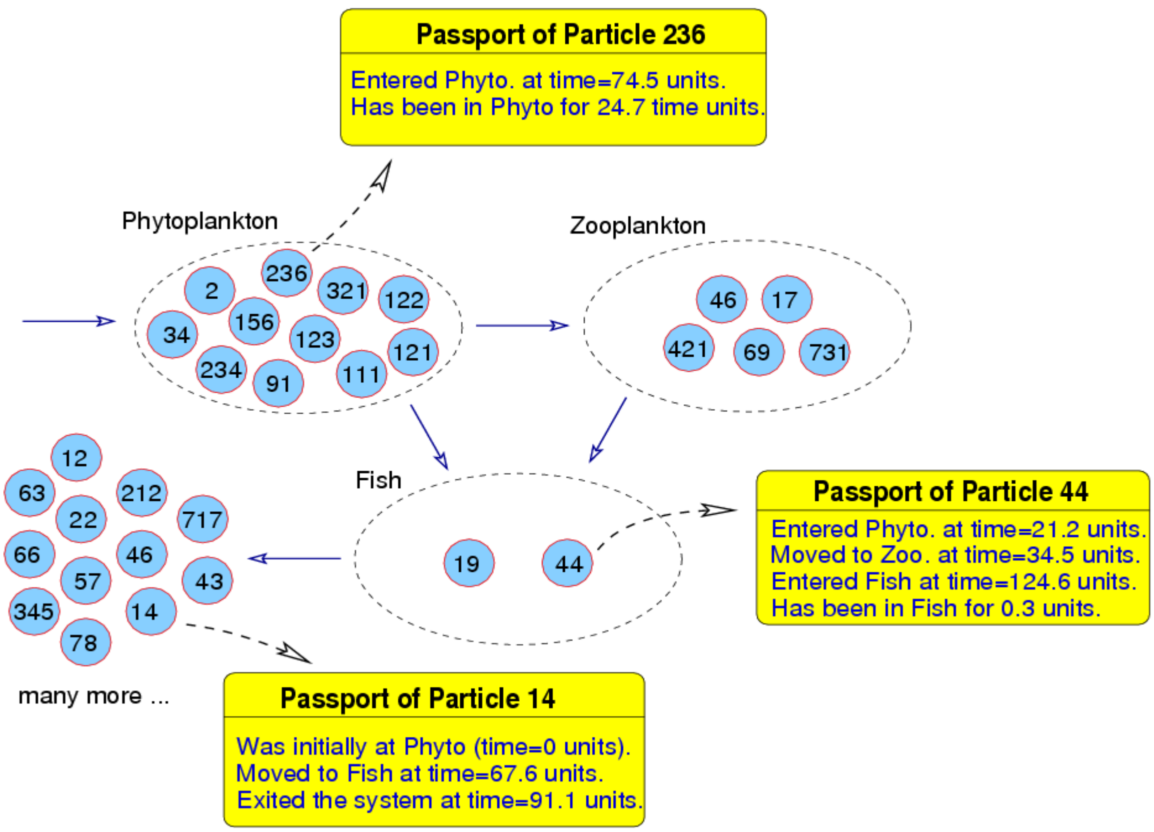


Figure 1. Hypothetical model depicting labeled discretized particles and their transport via NPT.

Knowing particle routing probabilities provides interpretive insight as to how ‘particles’ of energy or mass may move through a system before exiting. Kazanci and Tollner [21] mark and follow each discrete element, with the unique capability of attaching various identifying attributes to each particle as it routes through compartments maintaining a historical record of compartment contacts. NPT is essentially an individual-based (or agent based) method which deduces its rules on how an individual particle will move directly from the differential equation representation of the network model. NPT preserves causality. NPT is a stochastic method that is compatible with the so-called “master equation” [10-12]. In other words, the mean of many NPT simulations agrees with the differential equation solution. This property enables accurate comparison of NPT results with conventional simulation and analysis.

The Gillespie algorithm does not allow one to redirect particles based on information state. The pathway choice is dictated by probabilities arising from mean flows along particular pathways. Following the application of the improved Gillespie algorithm, one then completes a post path analysis. Each particle's identity and routing history (similar to international travelers' passport data; see Figure 1) can be further augmented with additional information documenting all desired aspects or properties of travel through the network. The travel history could also be used to gather additional routing information or as insight for other decisions. For example, one can log chemical energy changes for calculating exergy content variations, or steady-state models can be inspected to determine a distribution of a complete system and individual compartment residence times. NPT including the post path analysis weaves a stochastic nominalism into the organic holism and Newtonian determinism of ecological network modeling. Fath and Patten [5] articulated a series of orientor statements to describe the basic principles, which define the tendencies of directional development, self-organization and auto evolution. NPT provides an approach for mimicking and modeling the orientors. We then draw some analogies from statistical thermodynamics and compute some analogous terms as system indicators.

The focus of this work is to extend the NPT concept to include some measures analogous to those in statistical thermodynamics and to extend the concept to non-conserved information. We set out to model a student moving through a learning environment. The goal is to illuminate how to prepare engineers in a society that has moved away from the melting pot metaphor to the tossed salad societal metaphor. How does a student become educated as they move through four years of college is the question. Particularly in engineering, they move through a sequence of courses that cause students to apply previous coursework in new ways. As a rule, specific information presented in early years may be forgotten, but the experience of applying the facts and knowing where needed facts may be found, expands continuously as the student moves through the curriculum. It is intriguing to analyze students virtually moving through a network of knowledges as they mentally and in some cases physically revisit past course experiences. Said another way, the goal is to contemplate how we as faculty can help students recall and apply material that is prerequisite for a given area.

The objective of this presentation is to elucidate what NPT followed by post path analysis is in an education context. We present some anecdotal experience with how NPT and post path analysis with non-conserved information can help researchers and students to visualize what happens intellectually as students move through a college engineering curriculum. We mapped typical curricula onto four different ecological models to simulate the educational process.

Network Particle Tracking Analysis including Post Path Analyses

We constructed the four curriculum systems by starting with ecosystem models shown in Figures 2 and relabeling them as shown in Figures 3. Figures 3 represent the mapping of predominant aspects of the undergraduate engineering curriculum onto the given ecological system as indicated in the respective figures. Students enter near the top, and complete key lower level courses. Students then move to more advanced level courses. The loops back to lower level courses represent the application of concepts first introduced in the respective lower level courses. Courses with loops represents revisits to earlier parts of the course as time in the course progresses. The particles tracked in the analysis are students, as they move through the curricula. Students may revisit previous coursework, as shown by loops back to previous courses. Students may revisit earlier parts of current coursework, as shown by self-loops. Students may leave the curricula, as shown by the exit arrows not going to another compartment.

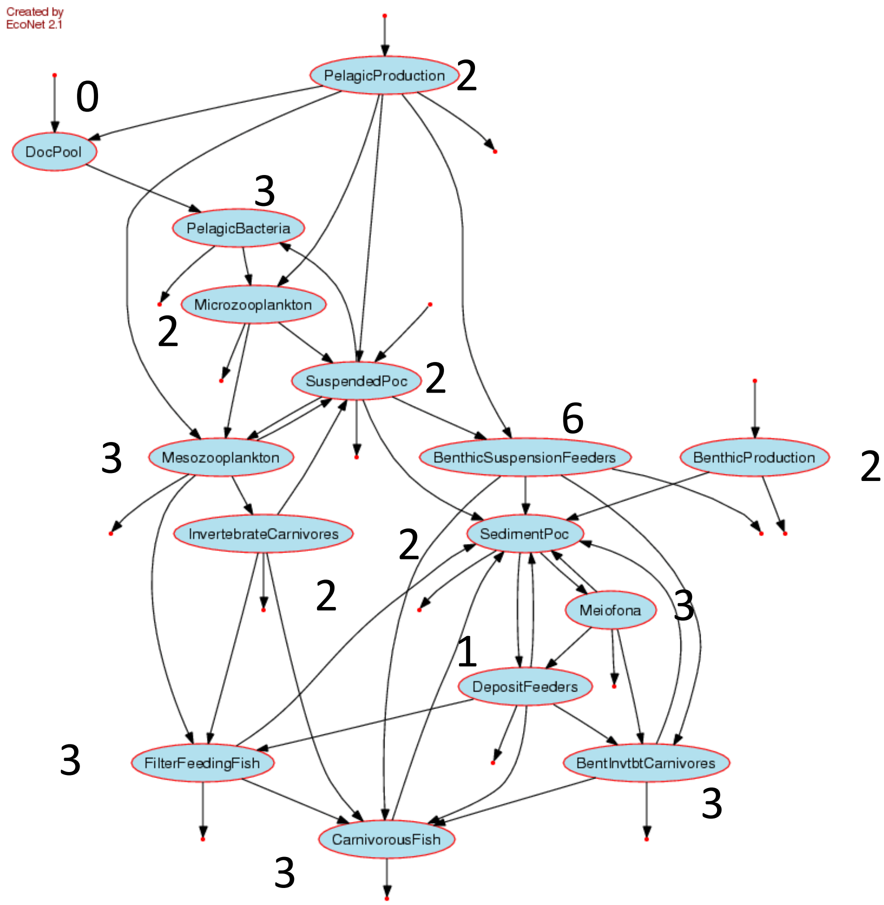


Figure 2a. EcoNet graphical output of energy flows in a generic marine ecosystem [24] showing the superimposed Jorgensen and Svirezhev [15] weighting coefficient beta values.

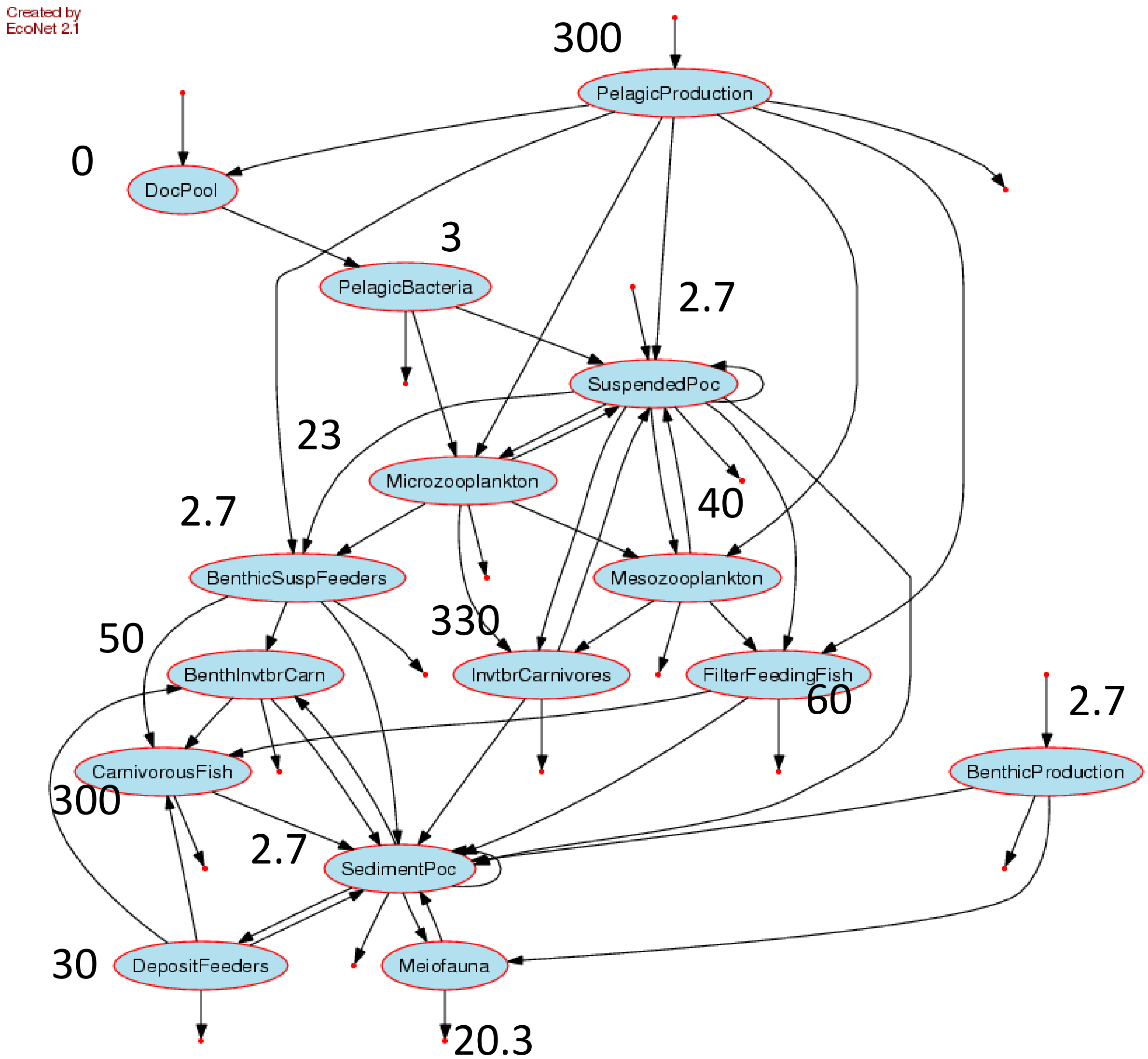
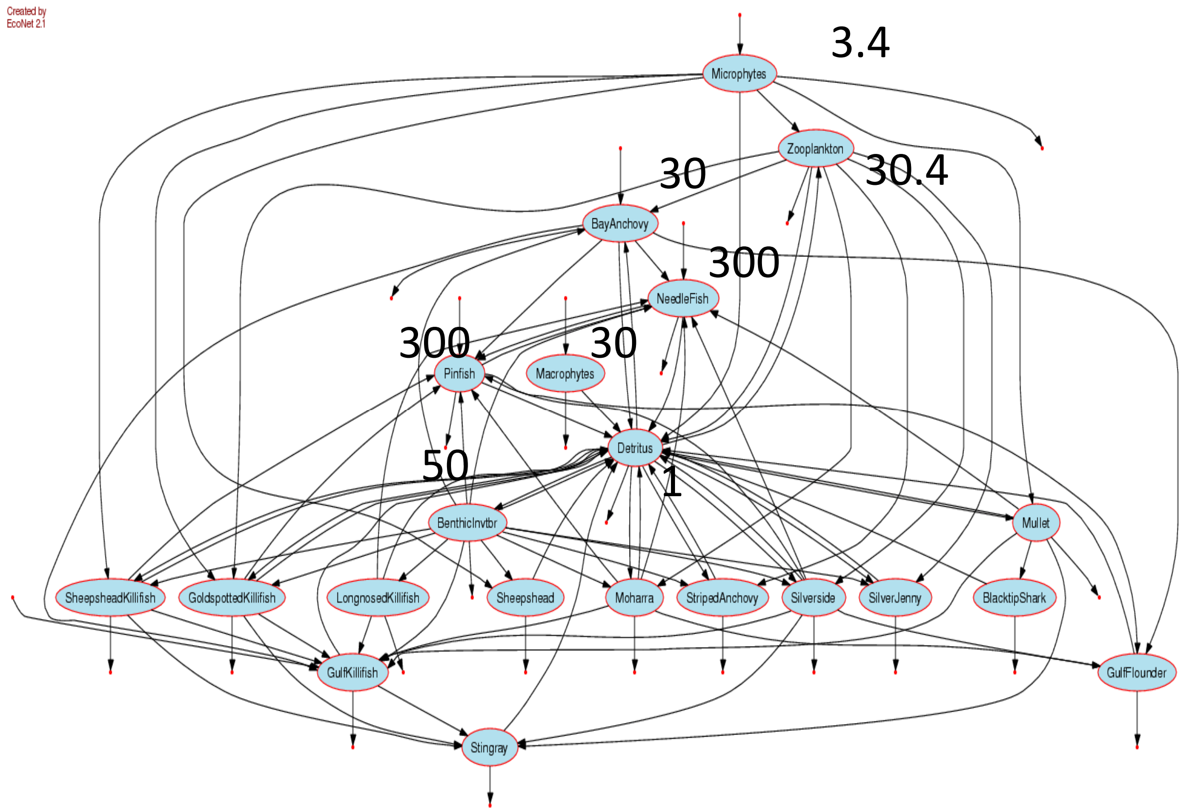


Figure 2b. EcoNet graphical output of energy flows in a Chesapeake Bay, USA, mesohaline ecosystem, USA [2] showing the superimposed Jorgensen and Svirezhev [15] beta values.



Beta = 300 unless otherwise noted.

Figure 2c. EcoNet graphical output of energy flows in Crystal River Creek tidal marsh in the vicinity of a nuclear power plant [23] showing the superimposed Jorgensen and Svirezhev [15] beta values.

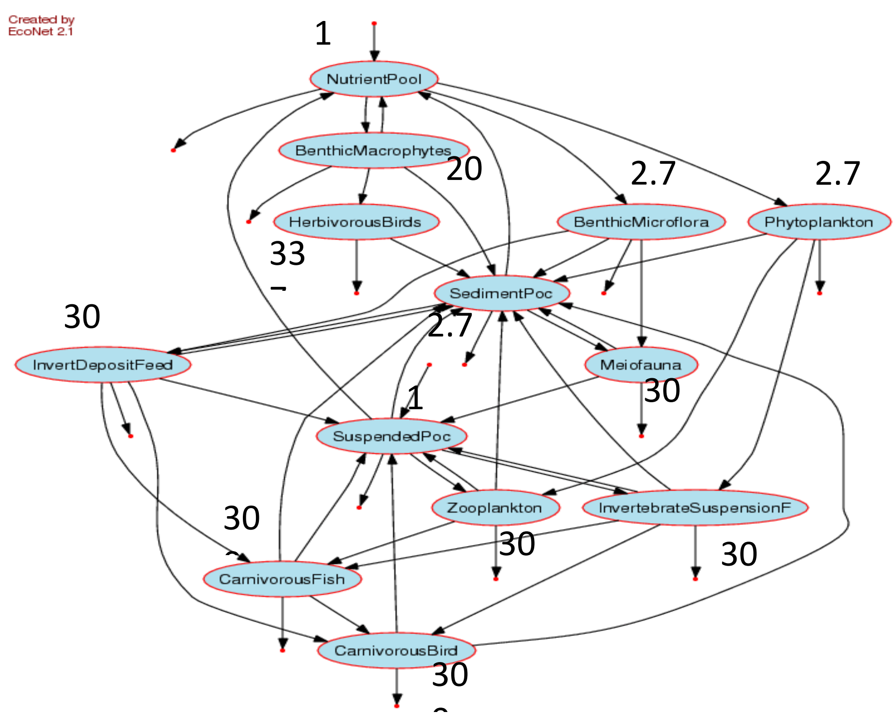


Figure 2d. Energy flow in a temperate estuary, Ythan Estuary, Aberdeenshire, Scotland [1] showing the superimposed Jorgensen and Svirezhev [15] beta values.

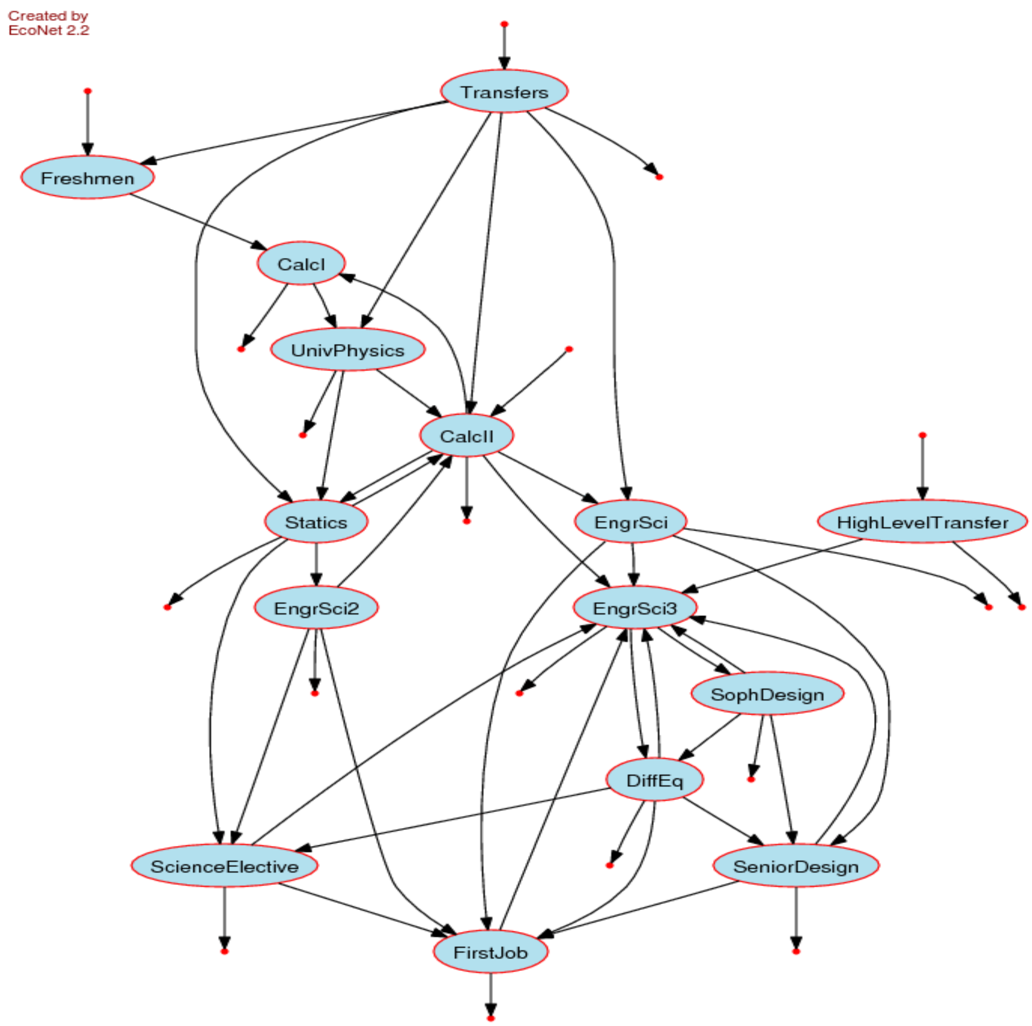


Figure 3a. EcoNet graphical output of curriculum system A, based on EcoNet graphical output of energy flows in a generic marine ecosystem [24].

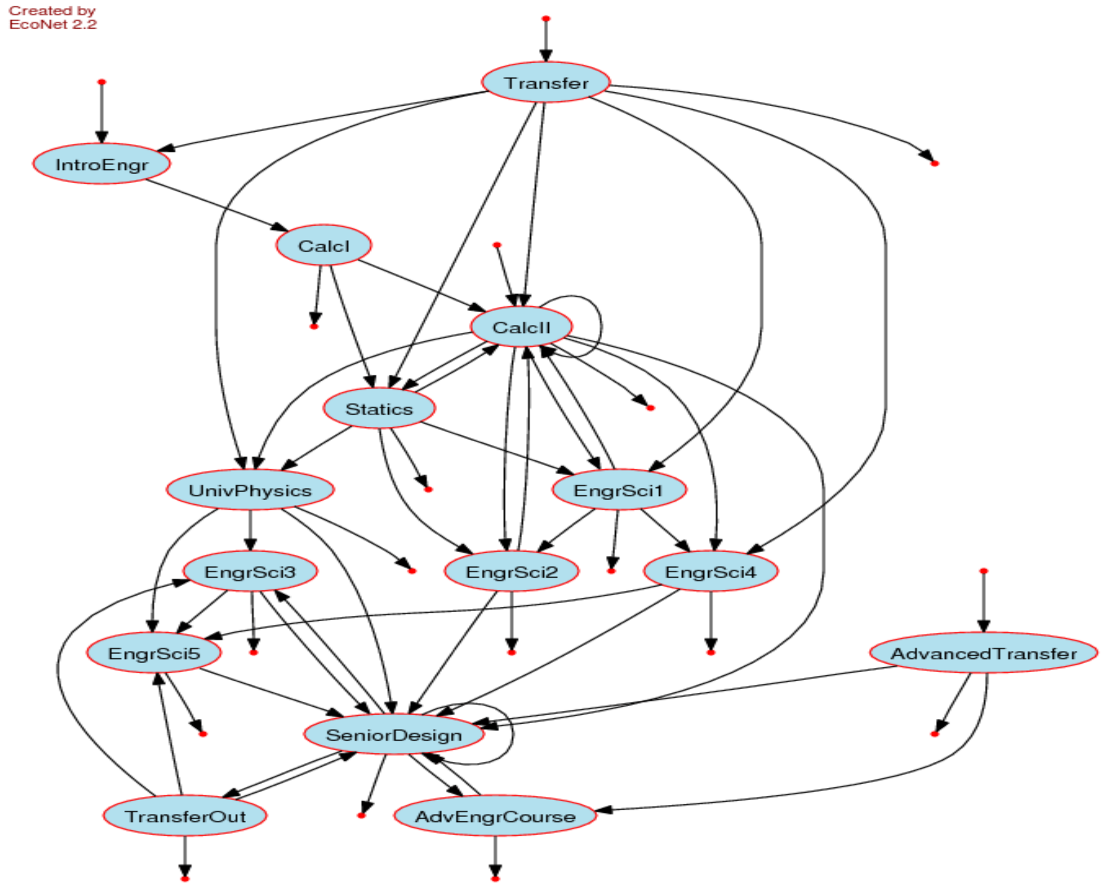


Figure 3b. EcoNet graphical output of curriculum system B, based on EcoNet graphical output of energy flows in a Chesapeake Bay, USA, mesohaline ecosystem, USA [2].

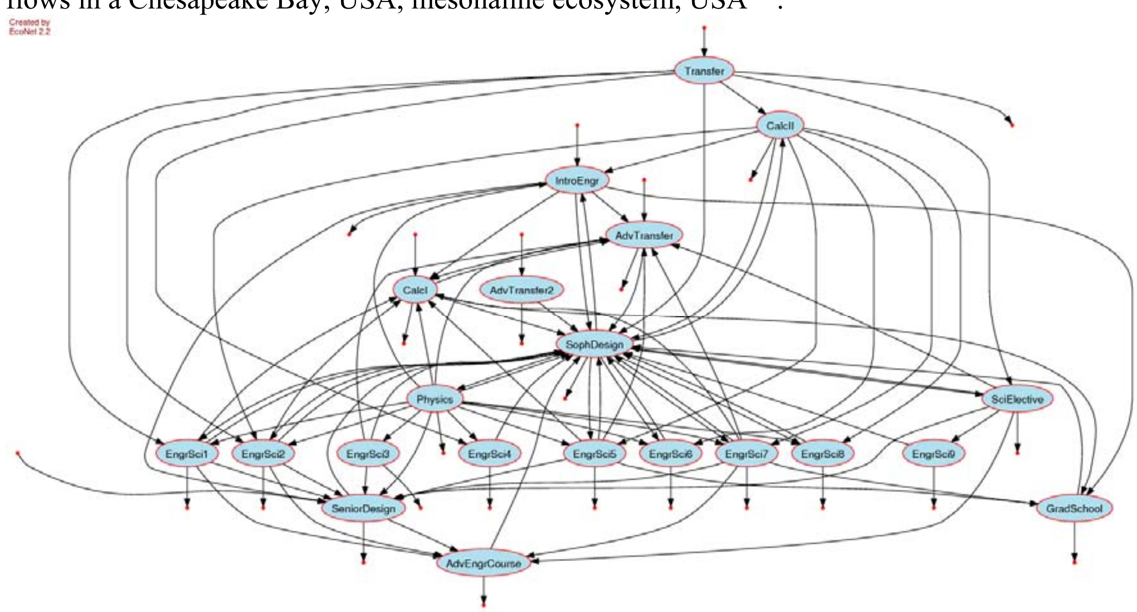


Figure 3c. EcoNet graphical output of curriculum system C, based on EcoNet graphical output of energy flows in Crystal River Creek tidal marsh near a nuclear power plant [23].

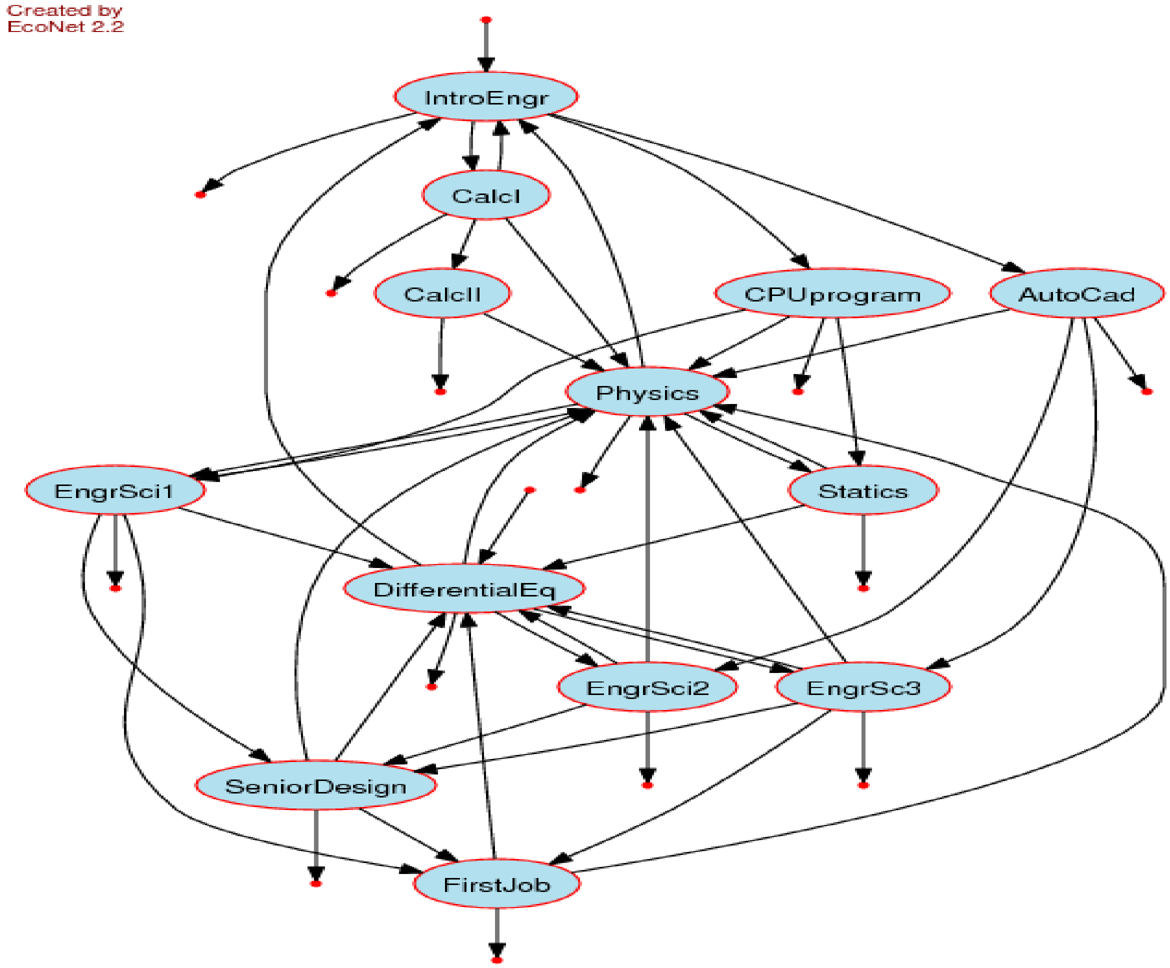


Figure 3d. EcoNet graphical output of curriculum system D, based on Energy flow in a temperate estuary, Ythan Estuary, Aberdeenshire, Scotland [1].

Table 1. Model summary showing ecological parameters.

Model	Model citation	Finn Cycling Index *	Indirect/Direct Effects **
A	Wulff and Ulanowicz, 1989	0.13	1.53
B	Baird and Ulanowicz, 1989	0.07	0.77
C	Ulanowicz, 1986	0.07	0.62
D	Baird and Milne, 1981	0.24	2.14

*see [8].
** see [13].

We study four different hypothetical curriculum models using NPT and post path analysis. First, we use NPT to study how particles, or intellectual content elements, are “distributed in the system” or “shared by compartments within the network”. With appropriate data, models like these could show how intellectual elements are distributed within a curriculum and they could quantify the strength of interactions among courses. To quantify this property, we focus on stored particles within a compartment at a given time. As illustrated in Figure 1, NPT provides the pathway history of each particle; therefore, we know how many other compartments a particle has been to previously. Table 1 shows the Finn cycling index and the ratio of Indirect/Direct effects ratio values for the model. The Finn cycling index reflects the extent of cycling in the respective models. The indirect/direct effects ratio indicates the effect of non-adjacent compartments on a given compartment. The indices are each computed from the compartmental adjacency matrix and material (intellectual information here) flow matrices. The indices do not depend on the nature of the particles flowing through the compartments. These indicators suggest that models A and D are similar (with substantial cycling) and that models B and C (with lower recycling) are similar.

The particles here represent quanta of mass or energy in the ecological context or individual fruits in the commodity distribution system. Loops represent directions of energy or mass flow based on analysis of what each species eats. Mass or energy is conserved in the ecological case. In the curricula context, particles represent the student’s physical and mental odyssey through curricula.

The components in the physical ecological networks represent possible ways to represent courses or modules in a curriculum. The inspiration behind the concept arose from drawing an analogy between energy flow through an ecological network or a commodity through a distribution system from the production field to the consumers’ refrigerator. Both systems are characterized by high losses at each step along the journey through the various nodes. That any given commodity generally flows with little or no recycling is one difference between the ecological model and the commodity flow model. A curriculum model could conceivably be anywhere between extensive cycling and essentially no cycling. The selected ecological models cover this gamut.

To apply this concept to a curriculum analysis, we mapped the key elements of a typical undergraduate engineering curriculum onto each of the four selected systems. The particles (quanta) are conserved, but particle attributes are not conserved. We hypothesized the following relations to model the respective quanta.

$$E(t)j=E(0)j + \text{Beta } i \ (1 - \exp(-t\%ji/tc\%i)) \qquad (1)$$

$$E(t)j=E(0)j \ \exp(-t\%ji/tc\%i) + \text{Beta } i \ (1 - \exp(-t\%ji/tc\%i)) \qquad (2)$$

$$E(t)j=E(0)j+1 \qquad (3)$$

Where

E(t)j represents the exergy or information of a particle “j” at time ”t”;

t%ji: residence time at compartment “j” for particle “i”;
Time constant (tc%i) = 1+Beta i/Heat loss(Qi), if Q = 0, tc=1; and,
Beta i is the exergy constant for compartment “i” from Jorgensen and Svirezhev [15]. The Beta coefficients were calculated based on the size of the typical genome of the organism representing the compartment.

Equation 1 simulates the forgetting of new information within each compartment. Equation 2 simulates the forgetting of initial and new information. Equation 3 represents a control where no information is forgotten. The time constant (tc%i) at compartment “i” corresponds to effectiveness of learning. The residence time (t%ij) corresponds to level of learning. The Beta coefficients (when not set equal to one) associated with the respective models are shown on Figures 2a through 2d. For equation 3, the beta of each compartment was set equal to one. We used the ecological beta values knowing that these coefficients need to be determined for a real curriculum, as do all the other coefficients. The beta coefficients represent weighting coefficients which increase with the level of the material in the curriculum. The practical significance of the beta coefficients remains to be determined.

Following the NPT and post path analysis of each ecological system, we applied equations 1-3 in a post path analysis. Equations 1 and 2 represent two different schemes for enabling mass to be lost or information to be forgotten. Equation 3 represents a scheme where visits to compartments are summed. Particles in the first two schemes may lose information depending on the residence time in the respective compartments. The initial exergy assigned is given by the value of the compartment (see Figures 2). Particles in the third system are incremented by one as they move through the system compartments.

For each compartment in each network, we create a series of plots based on all particles residing in that compartment after a time when the system has reached a quasi-steady state. A separate set of plots were created for each of equations 1 – 3. The analysis proceeds along the line of running the particle tracking on each of the systems for a time sufficient to bring the systems to a quasi-equilibrium state (e.g., the numbers of particles in each compartment are more or less steady). We then examine the history of each particle in a post path analysis using three different models.

Following the post path analysis with each of equations 1-3, we plotted the resulting exergy distributions as semilog plots of probability of having a given information exergy. Representative plots for two of the four systems (models C and D) are shown in Figures 4 and 5. Each compartment of each model is fairly well represented by a semilog plot. Higher information exergy values are indicative of quanta that had longer residence times in the systems. Equations 1 and 2 represent particles with low granularity in possible exergy values while equation 3 shows relatively limited variation in the quanta exergy state. Each point in the equation 3 plots represents multiple quanta while the quanta represented by equations 1 and 2 are distributed along a more continuous space. The trends shown in Figures 4 and 5 for models 4 and 15, respectively, are similar to those with models 2 and 3 (not shown). Each plot in Figures 4 and 5 (models C and D) along with the similar results for models A and B were broken into histograms of 30 bins each. These are analogous to quantum states in statistical thermodynamics. Looking at Figure 5c enables one to assess the number of compartments visited by a quanta since information exergy was conserved using equation 3. The effect of intellectual content (or quanta) change due to time effects was obvious with Figures 4a, 4b, 5a and 5b. These conditions associated with equations 1 (case a) and 2 (case b) resulted in more of a continuum of exergy levels due to forgetting and morphing. Each point in Figures 4c and 5c (equation 3) represents multiple quanta and thus appear granular compared to Figures 4a, 4b, 5a, and 5b.

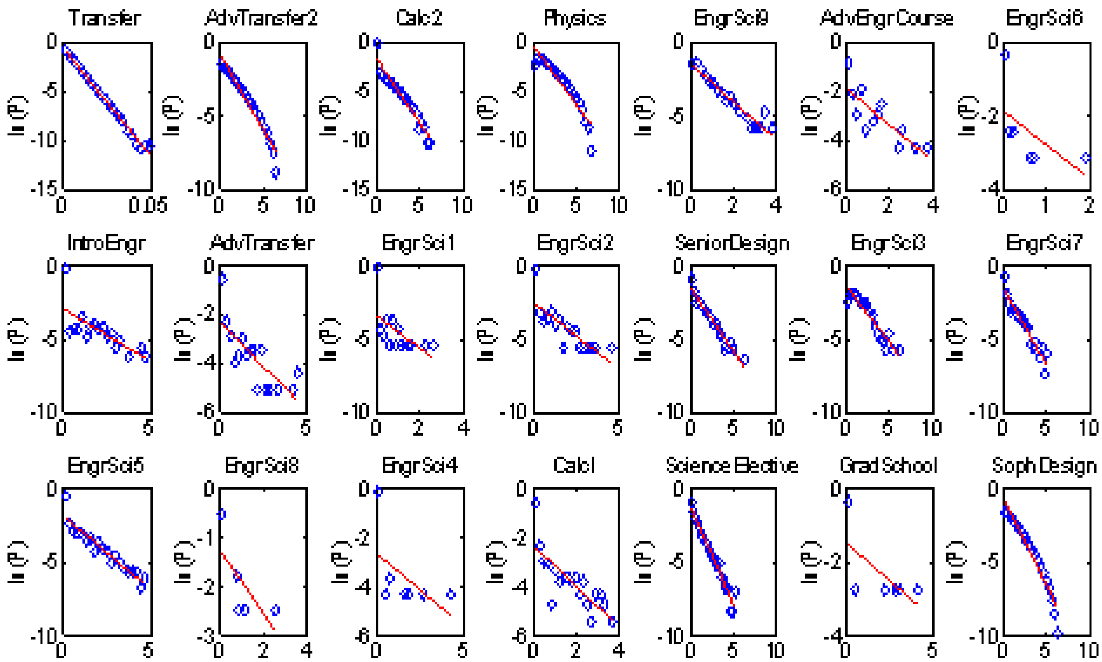


Figure 4a. Probability plots for each compartment of model C using equation 1.

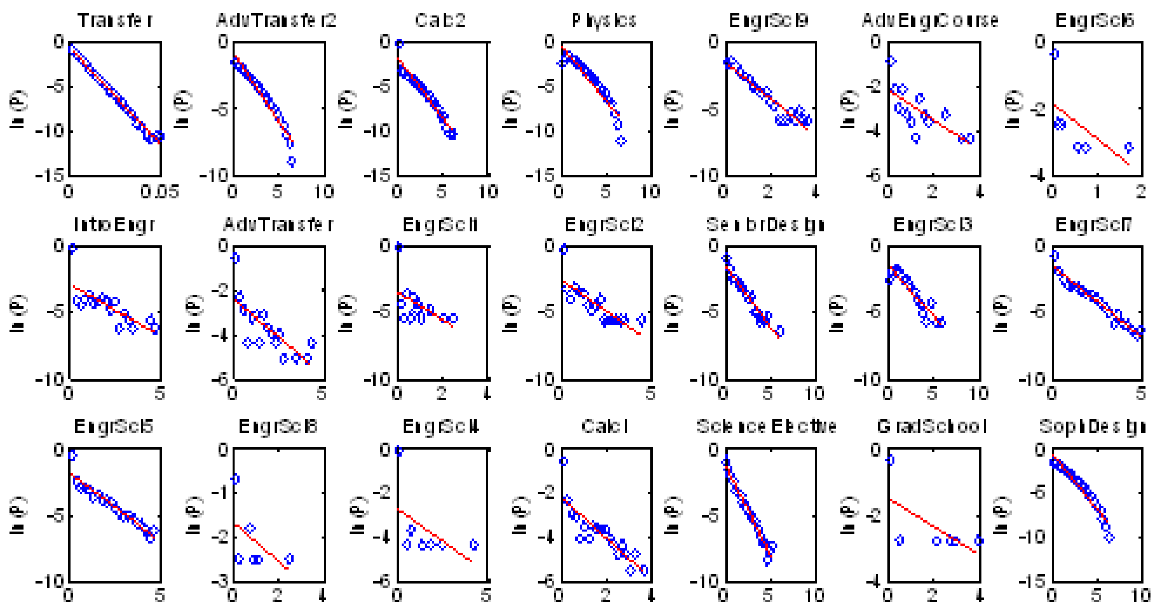


Figure 4b. Probability plots for each compartment of model C using equation 2.

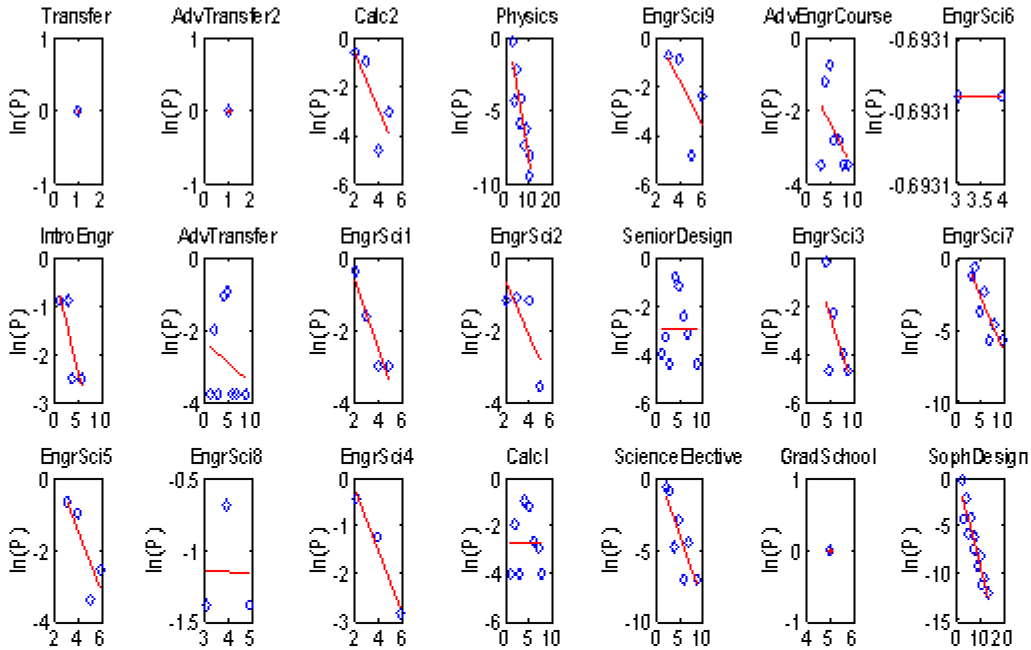


Figure 4c. Probability plots for each compartment of model C using equation 3.

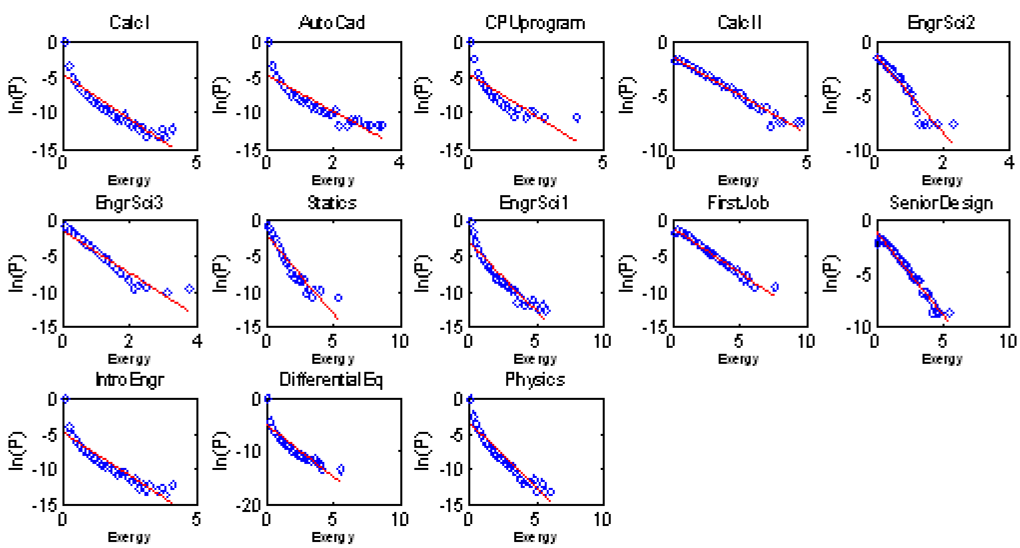


Figure 5a. Log probability plots for each compartment of model D using equation 1.

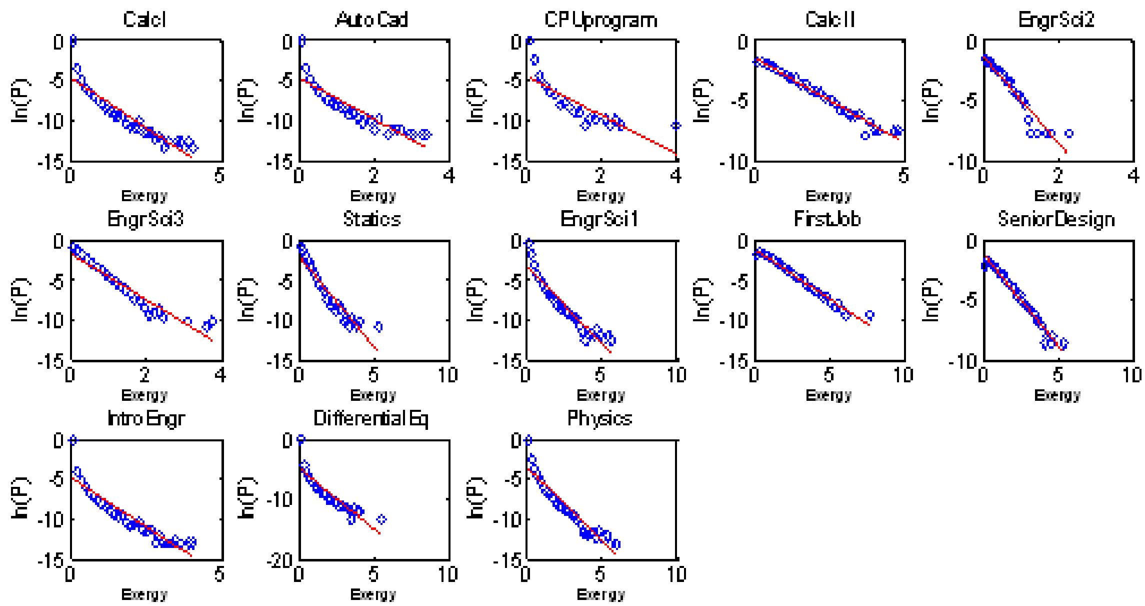


Figure 5b. Log probability plots for each compartment of model D using equation 2.

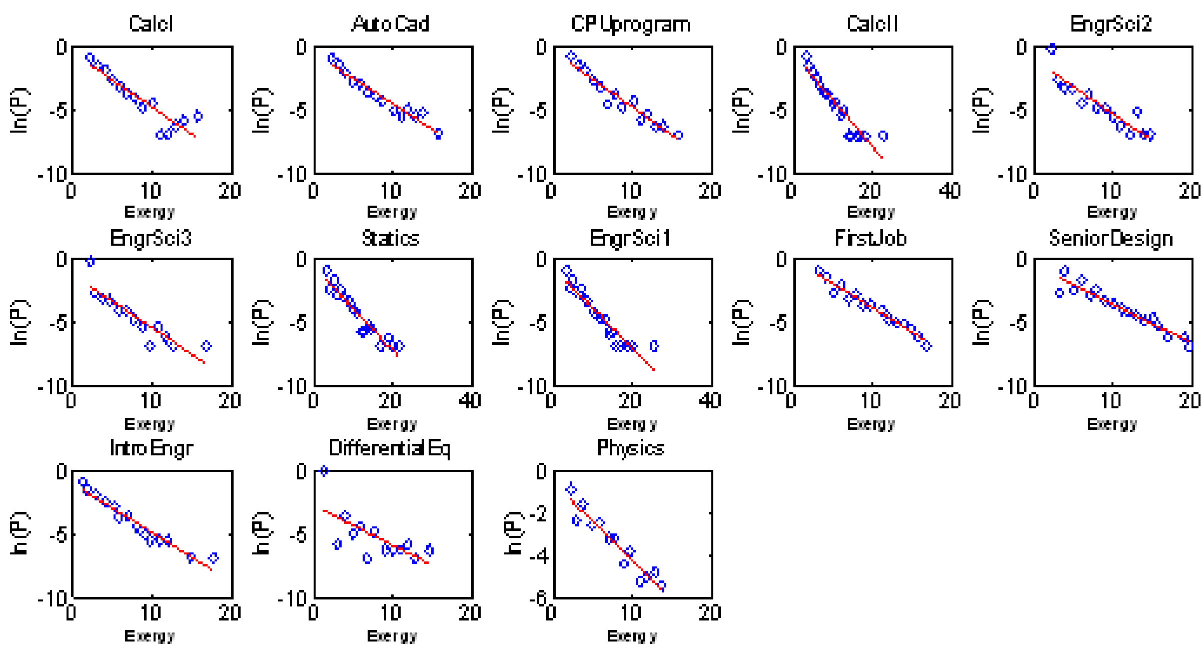


Figure 5c. Log probability plots for each compartment of model D using equation 3.

The continuum of points along the x-axis of each plot, particularly with equations 1 and 2, suggests a range of intellectual strength in each compartment. Ideally, we would like our curricula to produce only superior intellect. The various models seem to say that the curricula make little difference in the range of intellect developed when a degree of forgetting is involved. We have not addressed the retention question. Retention is clearly an issue when one considers all the exit points of the various modeled curricula. Retention questions require additional work.

We calculated the information entropy (S) and some other thermodynamic analogues using the following formulas [25] in equations 4 – 7. The information entropy S is given by equation 4.

$$S = \sum_{i=1}^{n} P_i ln P_i \qquad (4)$$

P_i is the probability of a particle having an exergy or information content of x relative to the total information in the compartment as found using the post path analysis and equations 1, 2 or 3. The probability Ω_i that a particle "i" is at a given state is given by equation 5.

$$\Omega_t = \frac{{X_t}^{N_t}}{N_t!} \qquad (5)$$

N_i is the number of particles exiting compartment "I" in bin "i", X_i is the number of particles in bin "i" having the same exergy or information. Ω is the probability that particle "i" is at a given state.

$$K = \frac{S}{\ln(\prod_{t=1}^{n} \Omega_t)} \qquad (6)$$

K is an analogue of the Boltzmann number. We may then compute an analogue of temperature from equation 7.

$$T = \frac{1}{K * B} = \frac{\ln(\prod_{t=1}^{n} \Omega_t)}{S * B} \qquad (7)$$

We show a summary of the temperature analogue and the information entropy in Table 2 for the post path analysis based on equation 1. The higher the temperature analogue, the higher the application frequency of concepts from the compartment in the respective network based on the number of compartmental linkages. The temperature analogue tended to correlate positively with the number of compartmental incoming or outgoing junctions, although the degree of cycling around the compartment was also influential. The results for equation 1 were similar to those of equations 2 and 3 (not shown). The temperature in a gas environment addresses the speed of an assemblage of gas molecules. Likewise, the temperature in a curriculum system could be a measure of the intellectual "heat" engendered by the curriculum.

Entropy is a measure of variety of information in a curriculum system. We did not see any particular trends with the computed entropy in the curriculum models studied.

The Finn cycling index and the Indirect/direct effects ratio quantify the inherent tendency of a curriculum to cause concepts to be revisited. The Finn cycling index and the Indirect/direct effects ratio for the models each suggests that curricula that require previously presented concepts to be revisited multiple times will be the curricula that show more compartments having higher temperatures.

The computed entropy values all ranged from zero to negative four. Zero means all particles in that compartment have the same E(t) values. The probability of being that value is one (P=1). Ln(p=1)=0. See eq. (4). This only happens for beta=1 case. Correlations between information entropy and other parameters were not obvious.

Table 2. Summary of Temperature and Entropy results for the four models using Equation 1 to represent the information quanta, where the information exergy states shown in Figures 4 and 5 were binned using 30 bins.

	Temperature analogue				Information Entropy			
Model No.-→ Compartment	A	B	C	D	A	B	C	D
AdvancedTransfer	**	0.87	-36.31	**	**	-1.84	-1.95	**
AdvEngrCourse	**	23.79	-27.88	**	**	-1.57	-2.29	**
AdvTransfer2	**	**	Inf	**	**	**	-2.71	**
AutoCad	**	**	**	Inf	**	**	**	-0.25
Calc I	28.68	Inf(A)	-32.84	Inf	-2.18	-1.16	-2.16	-0.22
Calc II	81.69	Inf	61.60	-6.69	-2.21	-1.29	-0.99	-2.49
Cpu program	**	**	**	179.85	**	**	**	-0.40
Diff Eq	-13.28	**	**	Inf	-2.50	**	**	-0.13
Engr Sci	71.54	99.91	-51.67	Inf	-2.00	-1.79	-0.68	-0.80
Engr Sci 2	1.29	5.35	-46.75	-2.69	-2.37	-1.76	-1.28	-2.31
Engr Sci 3	6.85	-5.70	-21.80	27.82	-2.29	-2.55	-2.78	-1.75
Engr Sci 4	**	-6.51	-61.16	**	**	-1.90	-0.46	**
Engr Sci 5	**	-6.98	-22.58	**	**	-2.77	-2.03	**
Engr Sci 6	**	**	-11.32	**	**	**	-1.23	**
Engr Sci 7	**	**	-15.45	**	**	**	-2.31	**
Engr Sci 8	**	**	-32.68	**	**	**	-1.59	**
Engr Sci 9	**	**	-14.27	**	**	**	-2.56	**
First Job	-12.85	**	**	-5.43	-2.37	**	**	-2.21
Freshmen	4.52	**	**	**	-1.78	**	**	**
Grad School	**	**	-50.17	**	**	**	-1.33	**
High Level Transfer	0.08	**	**	**	-2.13	**	**	**
Intro Engr	**	Inf	-69.93	Inf	**	-1.16	-1.03	-0.17
Science Elective	-7.89	**	-9.87	**	-1.56	**	-2.26	**
Senior Design	-15.18	255	-19.70	-7.04	-2.39	-2.04	-2.33	-2.42
Soph Design	-13.55	**	319.62	**	-2.64	**	-2.67	**
Statics	Inf	228	**	47.13	-1.89	-1.54	**	-1.45
Transfer Out	**	40.90	**	**	**	-2.14	**	**
Transfers	Inf	Inf	2.86	**	-1.83	-1.79	-1.98	**
Univ Physics	60.54	2.38	48.39	Inf	-1.83	-2.07	-2.72	-0.55

* Inf occurs because some bins have too many particles. The Ωs are infinitely high. See eq. (5). This causes K to approach zero. T=1/(K*B), thus goes to inf.
** Compartment did not occur in these particular curricula.

Validation strategy

The four curriculum models are presently highly arbitrary in that no hard data underlies any of the choices. One may use guidance from the process used to develop the underlying ecological models to develop inputs for the curriculum models. Ecologists apply the following procedure to develop models:

1. Identify the place and time desired to be modeled;
2. Identify the key environments and key species occupying the environments;
3. Identify the control volume containing the problem space;
4. Identify mass flows into and out of the control volume;
5. Identify mass flows into and out of each key specie type within the control space by performing an analysis of what is in the gut of the specie type;
6. Based on the gut analysis, identify the source and proportion of the contents coming from the various locations within the control volume;
7. Based on proportions and sources, one then constructs a network diagram and augments with flows and directions as aided using procedures such as those of Christian and Thomas [4]; and,
8. Using procedures of Tollner et al [22], Kazanci et al [17], and procedures given above, perform the NPT and post path analysis using appropriate beta values.

In order to map this process onto a curriculum analysis, items one through three are straightforward. One selects a curriculum in a particular school setting and identifies the key routes into and out of the curriculum. High school graduates and transfers are the key routes in and employment and graduate school are the key routes out for those who finish. Every course loses some students to other engineering or non-engineering programs.

Item 4 above requires special handling. The conserved entity being tracked is bodies; however, the primary interest is intellectual content. Student bodies, which are conserved, are carriers of the intellectual information that is modeled. The loss of a student represents a large body of intellectual content. The ecological models had much more loss than one should experience with a workable curriculum system. We cannot delineate at what point in the loss that a student leaves the curriculum. In addition, intellectual content is not a conserved quantity. As content is forgotten or is morphed into content with a larger scope, content is lost. Both content morphing and forgetting occur as students matriculate. Thus, we are dealing with non-conserved information in curriculum modeling. Equations 1 and 2 above enabled a combination of forgetting and morphing of information. Equation 3 was a conservative approach. This is somewhat demonstrated by the fact that the total accumulated information exergy was highest in equation 3 as demonstrated particularly by model D, equation 3 in Figure 5c.

Items 5 and 6 would require detailed sampling at the course and instructor levels. Syllabi and exams within each course would have to assess detailed content in order to provide a measure of what was presented and what was retained or not retained. Pretesting would be needed to see what prerequisite knowledge was retained at the subsequent courses in the curriculum. Extensive surveying of the student population is necessary. The approaches of Gattie et al [9] and Kellam et al [18] may facilitate the gathering of the needed data for an NPT-post path analysis. The extensive sampling is analogous to the gut analysis of item 6. The analysis of items 7 and 8 above would then be routine.

The first of two significant issues yet to be addressed is the fact that once a student leaves the curricula, the student is lost. Some may reenter via the transfer opportunities. We could interpret self-loops as drops and reentries in addition to the stated interpretation of revisits to earlier presented material. The retention issue is not well handled in this model as of yet. As presently configured, all the curricula shown represent an 'old school' approach to retention. As an admissions specialist (we would call them recruiters today) told some in my high school class back in the late 1960s, "If you can't cut the mustard, you have no business being here". Consistent with that approach, all the freshman classes and intro engineering classes were designed to eliminate non serious students and to identify potential graduate students. We can easily modify the loss flows such that the vast majority of losses occur at the terminal point. Such modifications would be more consistent with current approaches to producing STEM talent and retaining students in curricula. Reflecting these contemporary ideas in the model will be a subject of future work.

The second issue yet to be addressed is that of appropriate assignment of beta values for curricula. We used the ecological values in this preliminary work. One might assign values corresponding to the level of the course compartment in the curricula. Major courses might have higher beta values as opposed to general education electives (for engineering students). The final temperature results did not seem to be overly sensitive to the beta values.

Summary and salient implications

NPT is a discrete, quasi steady state, input-output analyses based on conserved currency (e.g., energy, mass) movement through compartments (described by states), each with input-output environs that are connected. NPT discretizes the transported currency in the NEA model into 'particles' or 'quanta'. The particles acquire individual histories as the particle moves through the system prior to dissipation or exit. The NPT post processing approach represents a way of quantifying curricula where students are conserved but the intellectual information is non-conserved. The post path analysis represented by equations 1 and 2 above was a strategy to enable a non-conservative analysis.

The significance of cycling confirms that frequent reinforcement of concepts is necessary and valuable for learning improvement. The Finn cycling index provides a measure of cycling on a system wide basis. The indirect/direct effects ratio gives a measure of how intellect may grow due to tangential reasons as opposed to purposed learning. The curriculum analysis outlined above objectively quantifies the importance of a particular curriculum block based on the paths and flows in and out of the compartments via the temperature analogue.

Another finding of this work would seem to be that curricula configuration is not as influential as we would like. The work would support that good students will do well regardless of the curricula. This may be indicative that our model now represents the goal of identifying the numbers of extremely good students.

The ability to retain students is of increasing interest, and this question needs further study. One feature of ecological models is that of dissipation. Mapping curricula onto ecological models made the implicit assumption that curricula would lose students as ecosystems dissipate energy. Future work is needed to identify how reduction of losses would influence the analysis.

The data analysis required to define the NPT curriculum model is substantial. Given the degree of numbness nowadays to surveys in general, one wonders how successful one would be in actually obtaining the needed data. In other words, we do not see this analysis as a panacea that solves and documents all curriculum issues. A partial analysis of a curriculum using some well-targeted survey instruments may be the most effective approach overall.

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