Article

CPM Stability in Complex Projects and Systems

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Abstract

Critical Path Method is a prevalent project management modeling software; yet CPM methods fail in complex projects. There is a gap in understanding why and how CPM fails. This article addresses these gaps in understanding CPM failure, establishing morphology and risk as the influencing parameters of complex network stability while highlighting the limitations of CPM modeling and falsifying the applicability of established mathematical tools for analyzing complex network stability, and ultimately falsifying the applicability of CPM to complex systems. The research is carried out through numerical experiments and case study analysis, utilizing statistical methods, descriptive statistics, network analysis, data entropy, criticality index (CI), and Principal Component Analysis. This research contributes to the falsification of a stalwart paradigm and offers new insights into complex network modelling, limitations, and management.

Keywords: complex projects management; critical path method (CPM); infrastructure management; complex networks stability.

1. Introduction

Critical **P**ath **M**ethods (CPM) are widely used in civil engineering; CPM is often required by contract [1]. Standard CPM software benefited from decades of development, shaped by extensive application, feedback, and refinement. These tools evolved to integrate scheduling, costs, cash flow, constraints management, manpower, and resource allocation to produce various outputs, including block diagrams, Gantt charts, cash flow diagrams, and resource histograms, among others. However, despite their seemingly coherent, productive, and detailed nature, these systems often fall short in representing project complexities [2].

The literature suggests that CPM is "unsuitable for construction management" [3], yet the reasons for this inadequacy are not fully understood. Gómez-Cabrera et al (2024) [4] attribute CPM inadequacy to uncertainty and risk, while Eppinger and Browning (2012) [5] contend that failures arise from coupled activities modelling, Shen et al (2022) [6] highlight the complexity introduced by the connections between elements, Ballesteros highlighted changes introduced to networks that generate non-linear effects [7] while CPM is a linear program. Newman et al [8] added the power law distributions of faults, and Reason [9] introduced the concept of imported risk and latent faults. Pinto and Slevin

[10] suggested that failures originate in information. In line with [11], Yonat [12] emphasized the role of information systems, and [13] pressed the influence of sociological factors such as leadership. General system theory approach applications, such as Liu et al. (2024), [14] add the effects of other systems, and Dehmer and Moskowitz (2011) [15] the significance of entropy. The current research adds expertise as a factor influencing morphology and explores the link between expertise and risk [4]. CPM networks are feedforward networks where activities are activated when reached and deactivated after being passed; activated activities form a local **morphology** which is a reaction to chance and necessity [16]. In real life scenarios there is a Quantum dynamical effect of decision making [17] that relates to possibilities beyond those incorporated in the decided upon baseline design; attesting to time management practice where potentiality coexists with actuality.

All the above indicate potential causes for failure, providing insight into why these factors may undermine CPM, but not **how** they contribute to CPM's failure.

The objectives of this research are to demonstrate CPM failure, to falsify the applicability of stability criteria and modeling paradigms, to explore under what terms Critical Path (CP) may be predicted, to address both how and why CPM fails, and ultimately, to propose a viable use for CPM in management.

The layout of this article is as follows: this introduction is followed by a definitions section, and a method and data section which details the experiments, case studies, and explicatory parameters. Next, the hypothesis is introduced, followed by the presentation of experimental and case study results. The falsification section comes next, where the explicatory parameters and procedures are critically evaluated. The Discussion section provides summary, meaning, insights and inferences on topics such as network morphology and its effects, viability kernels, expertise, butterfly effects, the impact of synchronization and off-site prefab production on entropy, reification, hypothesis validation, strategies for managing complex systems, and potential use for CPM. Finally, the Summary and Conclusion section highlights the salient findings and contributions of this manuscript.

2. Definitions

#	Definition	Equation
Adjacency matrix	Adj. Matrix (A) is a matrix where an entry represents an edge	
Attractors	function as the minimum or maximum energy states that a network tends to gravitate towards. These attractors represent metastable configurations.	
Barriers	errors such as materials deficiency and design mistakes from entering the system [18]; such are quality control measures, peer review and praxis. Once barriers are penetrated CPM durations and costs overflow.	
CPM	A directed network representation of projects modeled as a finite state machine with binary activation and fixed Markovian states. The primary objective of this model is to identify the 'critical' path.	
Critical Path (CP)	**D**efined as the longest path through the network.	
Criticality index (CI)	The critical path (CP) likelihood.	

DSM	**D**esign **S**tructure **M**atrix, direction is 'from' horizontal 'to' verticals.	
Edges	precedence directed associations between activities.	
Eigen ratio	$\frac{\vartheta_{max}}{\vartheta_1}$, $where\ \vartheta$ are eigenvalues of the Laplacian	(1
Entropy	Data entropy: $Etropy = -\sum_r p_r\ ln(p_r)$ Where p is the probability of state r. Here, in researching CPM, we are interested in CP as a state indicator and in CI as its probability estimator. In this manuscript we calculate graph entropy using CP likelihood distribution as an estimator of CP probability distribution (information functional [19]). For the use of Shannon entropy rather than nonlinear entropy please refer to [12]	(2
Faults	Change agents that penetrated the systems' barriers [12]. Faults generate cost and duration overflow. Uncorrected, faults multiply, magnify, and propagate to avalanche.	
Faults magnitude	is a power function [12].	
Imported Risk	The risk introduced into a system through external sources, such as subcontractors and supply chains, the contagion of systemic financial risks [20], as well as through company processes and information networks. Design feeds faults to all, embeds latent faults and causes rework.	
Laplacian	$\mathfrak{L} = I \cdot d - A$: The non-directed (symmetric) Adj. Matrix (A) subtracted from a unit matrix (I) factored by the networks' nodes degree vector (d).	(3
Laplacian Eigenvectors	The graph spectrum calculated for the non-directed graph weighted Laplacian.	
Laplacian Variance (directed Graph)	$\sigma_\mu^2 = \frac{1}{d^2(N-1)}\sum_{i=2}^{N}\lvert\mu_i - \bar{\mu}\rvert^2$ where "d" stands for degree and μ_i are the Laplacian eigenvectors values.	(4
Minimum networks	In this context, minimum networks refer to networks that contain only the essential information required for systems teleonomic function.	
Morphology	generates, multiplies, inflates, and propagates faults.	
Nodes	in this work activities are in the nodes.	
Ntropy	Normalized entropy parameter suggested in this work:	(5

	$Ntropy = -k_N \sum_r p_r\, ln(p_r)\,,\ for\ p(N) = \frac{1}{n},\ k_N = \frac{1}{\sum_1^n \frac{1}{n} ln \frac{1}{n}} = \frac{1}{ln\,(n)}\ ,\ k_N = max\,(entropy)$	
Outdegree	Node's number of outgoing edges.	
PDF	**Faults P**robability **D**istribution **F**unction is Log-Normal (LN) [21].	
Power function	(ax^{-b}) is the magnitude distribution of the LN PDF [12], it is a scale-free function, it entails complexity; The power factor 'b' is a phase parameter; it is correlated with entropy. Time and cost have Power functions magnitude distribution functions.	
Replicator equation	In evolutionary Graph Theory [22], $\dot{x} = F(x_i \| e_{i,j}) - \sigma \sum_{j=1}^{n} Ꝉ_{ij} A_j$ Where x_i is the state variable of the weighted adjacency Matrix (A), L is the Laplacian. $F(x_i(t))$ is the CPM recursive optimization procedure. The threshold is: $F(x_i) \leq \sigma \sum_{j=1}^{n} Ꝉ_{ij} A_j$	(6 (7
Synchronization	Concurrent activities and hammock activities in construction, loops in design. In production lines, synchronized activities are activities with the same frequency.	
Systemic Risk	manifests in **faults**' PDF.	
Time	Time is discrete, here the time unit 1 week.	
Viability Kernel	$e_{i,j}(t) \in K$ Here K is the group of allowed edges between activities i,j.	(8
WBS	**W**ork **B**reakdown **S**tructure.	

List of Abbreviations:

abs	Sign (x)*x
CI	**C**riticality **I**ndex
CPM	**C**ritical **P**ath **M**ethod
CP	**C**ritical **P**ath
DSM	**D**esign **S**tructure **M**atrix
fft	**F**ree **F**ourier **T**ransform
LN	**L**og-**N**ormal
PDF	**P**robability **D**istribution **F**unction
PCA	**P**rincipal **C**omponent **A**nalysis
Stdv	**St**andard **D**eviation
Var	**V**ariance
WBS	**W**ork **B**reakdown **S**tructure

3. Data and Methods

The methodology is falsification using numerical data analysis of numerical experiments and case study databases. Karl Popper in his Philosophy of science substantiated that the scientific method relies on falsification of theories rather than on classical inductivist methods. There is asymmetry between verification and falsification: no number of positive experimental testing outcomes can confirm a scientific theory, but a single counter-example is a decisive refute. Following Poppers direction, we supply one falsifying example to every theory its applicability is negated [23].
The methods are data analysis using tools such as network analysis (morphology, attractors, degree distribution), PCA (eigen analysis, superposition, clusters, Stdv.), statistics (PDF, power functions, entropy, ..), descriptive statistics (CI, fft, spectral clustering), linear algebra (Laplacian), and CPM (critical paths). Expert intake [24] supplies insights and relates industry-related interpretation to mathematical products.

Numerical experiments, data, and parameters:

3.1. Experiments

- Five DSM generated timetables (portrayed in section 5.1. Experiments)
- Three decision rules for correction of faults.
- Two PDF.
- Iterations: 6, 24, 30, 200, 500 repetitions.

3.2. Case Studies data

Table 1 portrays the details of the case studies' data sources and availability.

Table 1: Discipline and data sources of the case studies

#	Discipline	Project Description	Catalogue	Availability
I	Control	Pumping station Jebeke	C-2012-13	[25]
II	Building	a House	C2011-10	[25]
III	infrastructure	Windfarm	C-2011-13	[25]
IV	Prefabrication	Prefabricated construction	Shen et al. (2022)	[6]

3.3. Explicatory Parameters Subjected to Falsification

- Number of edges
- Degree
- Laplacian phase parameter '**b**'
- Alternative CP
- Criticality Index (CI)
- Replicator equation
- Entropy / Ntropy
- Stdv
- Eigen-ratio
- Eigenvalue Stdv
- Principal Component Analysis (PCA) Vibration modes: Eigenvector, eigenvalue refractions
- synchronization
- Simulations

4. Hypothesis

CPM networks evolution and stability are decided by **morphology** and **statistics**.

Morphology is the info-system's morphology, and fault statistics is system response statistics [12].

5. Experiments, Case Studies AND Results

The experiments involve five different representations of the same project. The differences between these representations are small, remaining well within acceptable variations of the same project management plan. CPM 2-CPM5 may be considered as sensitivity analyses of a baseline blueprint.

5.1. Experiments

CPM1 Figure 1 is a 24 activities adjacency matrix of a one-story conventional house construction project. In this model, 'n' iterations correspond to a project involving 'n' townhouses built sequentially. The adjacency matrix is weighted according to activity durations, with the initial duration set at 1 week.

CPM1		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	duration
ground works	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
foundations	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
base	3	0	0	1	1	0	1	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1
electricl inst	4	0	0	0	1	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1
instalation	5	0	0	0	0	1	0	1	1	0	1		1	0	0	0	1	0	0	0	0	0	0	0	0	1
piers	6	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
walls	7	0	0	0	0	0	0	1		1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
ceiling	8	0	0	0	0	0	0		1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0	0	1
plaster	9	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1
flooring	10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
Air conditioning	11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1
kitchen	12	0	0	0	0	0	0	0	0	0	0	0	1	0	0		1	0	0	0	0	0	1	0	0	1
communication	13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1
security	14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1
control	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0		1	0	1
paint	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	1
instalation outdoors	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1
plaster outwalls	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1
development	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1
gardening	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1
isoltion	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1
sanitary instalations	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
electrical instalations	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
Delivery	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1

Figure 1. CPM1 Adjacency matrix + initial durations.

CPM2 is CPM1+ an added noncritical activity (activity 19 Figure 2).

CPM3 is CPM2 with added critical activity (activity 9, Figure 3).

CPM4 is CPM3 with an edge deletion and 7 edges location change, to correlate it with an expert-engineer produced Gantt (Figure 4).

CPM5 is CPM4 with an edge deletion and three edges location change to adjust to the critical path produced by an expert (Figure 5).

CPM2		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	duration
ground works	1	1	1			1																					1
foundations	2		1	1																							1
base	3			1	1		1	1						1				1			1						1
electricl inst	4				1						1	1	1	1	1	1	1										1
instalation	5					1		1	1		1		1				1										1
piers	6						1	1	1																		1
walls	7							1		1	1																1
ceiling	8								1	1	1	1										1	1				1
plaster	9									1		1					1			1							1
flooring	10										1						1			1							1
Air conditioning	11											1				1											1
kitchen	12												1				1							1			1
communication	13													1		1											1
security	14														1	1											1
control	15															1									1		1
paint	16																1							1	1		1
instalation outdoc	17																	1	1		1						1
plaster outwalls	18																		1	1	1						1
Aluminium instalati	19																			1						1	1
development	20																				1	1					1
gardening	21																					1			1		1
isoltion	22																						1	1			1
sanitary instalatio	23																							1		1	1
electrical instalati	24																								1	1	1
Delivery	25																									1	1

1

Laplacian full

2

																									eigenvalues(
2	-1	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			0
-1	2	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.840078
0	-1	7	-1	0	-1	-1	0	0	0	0	0	-1	0	0	0	-1	0	0	-1	0	0	0	0	0	0.9374339
0	0	-1	8	0	0	0	0	0	-1	-1	-1	-1	-1	-1	-1	0	0	0	0	0	0	0	0	0	1.1526831
-1	0	0	0	6	0	-1	-1	0	-1	0	-1	0	0	0	-1	0	0	0	0	0	0	0	0	0	1.7319905
0	0	-1	0	0	3	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.8322978
0	0	-1	0	-1	-1	5	0	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.107711
0	0	0	0	-1	-1	0	7	-1	-1	-1	0	0	0	0	0	0	0	0	0	-1	-1	0	0	0	2.3919222
0	0	0	0	0	0	-1	-1	5	0	-1	0	0	0	0	-1	0	0	-1	0	0	0	0	0	0	2.5344322
0	0	0	-1	-1	0	-1	-1	0	6	0	0	0	0	0	-1	0	0	-1	0	0	0	0	0	0	2.7146815
0	0	0	-1	0	0	0	-1	-1	0	4	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	2.997796
0	0	0	-1	-1	0	0	0	0	0	0	4	0	0	0	-1	0	0	0	0	0	0	-1	0	0	3.5163656
0	0	-1	-1	0	0	0	0	0	0	0	0	3	0	-1	0	0	0	0	0	0	0	0	0	0	3.981837
0	0	0	-1	0	0	0	0	0	0	0	0	0	2	-1	0	0	0	0	0	0	0	0	0	0	4.1613158
0	0	0	-1	0	0	0	0	0	0	-1	0	-1	-1	5	0	0	0	0	0	0	0	0	-1	0	4.8526581
0	0	0	-1	-1	0	0	0	-1	-1	0	-1	0	0	0	7	0	0	0	0	0	0	-1	-1	0	5.0528096
0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	-1	0	-1	0	0	0	0	0	5.2409965
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	3	-1	-1	0	0	0	0	0	5.5185629
0	0	0	0	0	0	0	0	-1	-1	0	0	0	0	0	0	0	-1	4	0	0	0	0	0	-1	5.9342896
0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	-1	0	4	-1	0	0	0	0	6.5516779
0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	-1	3	0	0	-1	0	6.9982411
0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	-1	0	0	7.7513334
0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	-1	0	0	0	0	0	-1	4	0	-1	8.1143787
0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	-1	0	0	0	0	-1	0	0	4	-1	9.3220231
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	-1	-1	3	9.7624843
																					eigenratio			$\frac{\theta_{max}}{\theta_1}$ =	11.620926

3

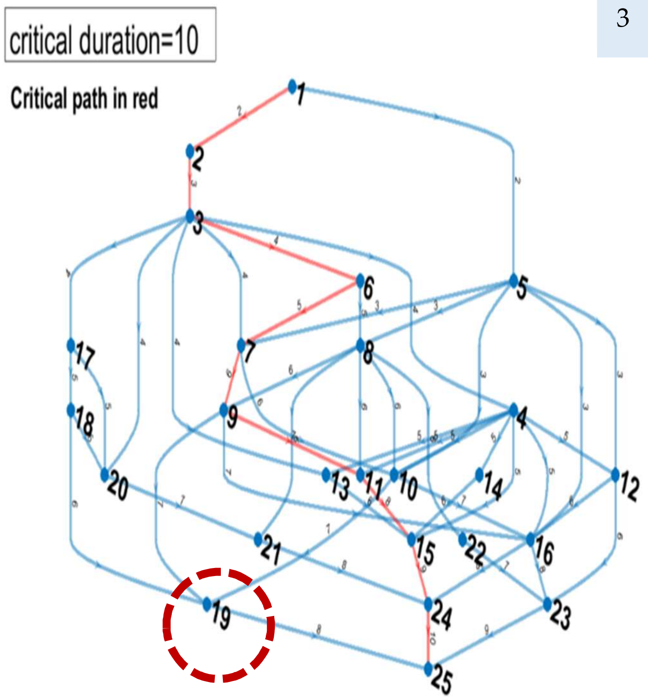


Figure 2. CPM2 Adjacency matrix (1), Laplacian(2) and node 19 location and CP (3).

Figure 2.2 presents eigenvalues generated from a non-directed weighted Laplacian. The directed graph is a sub-graph and therefore the outcome applies to it too. The non-directed graph has a relevant meaning of an information network, a meaning further discussed hereby.

In Figure 2.3 the edges are weighted by duration. This applies to all networks in this study.

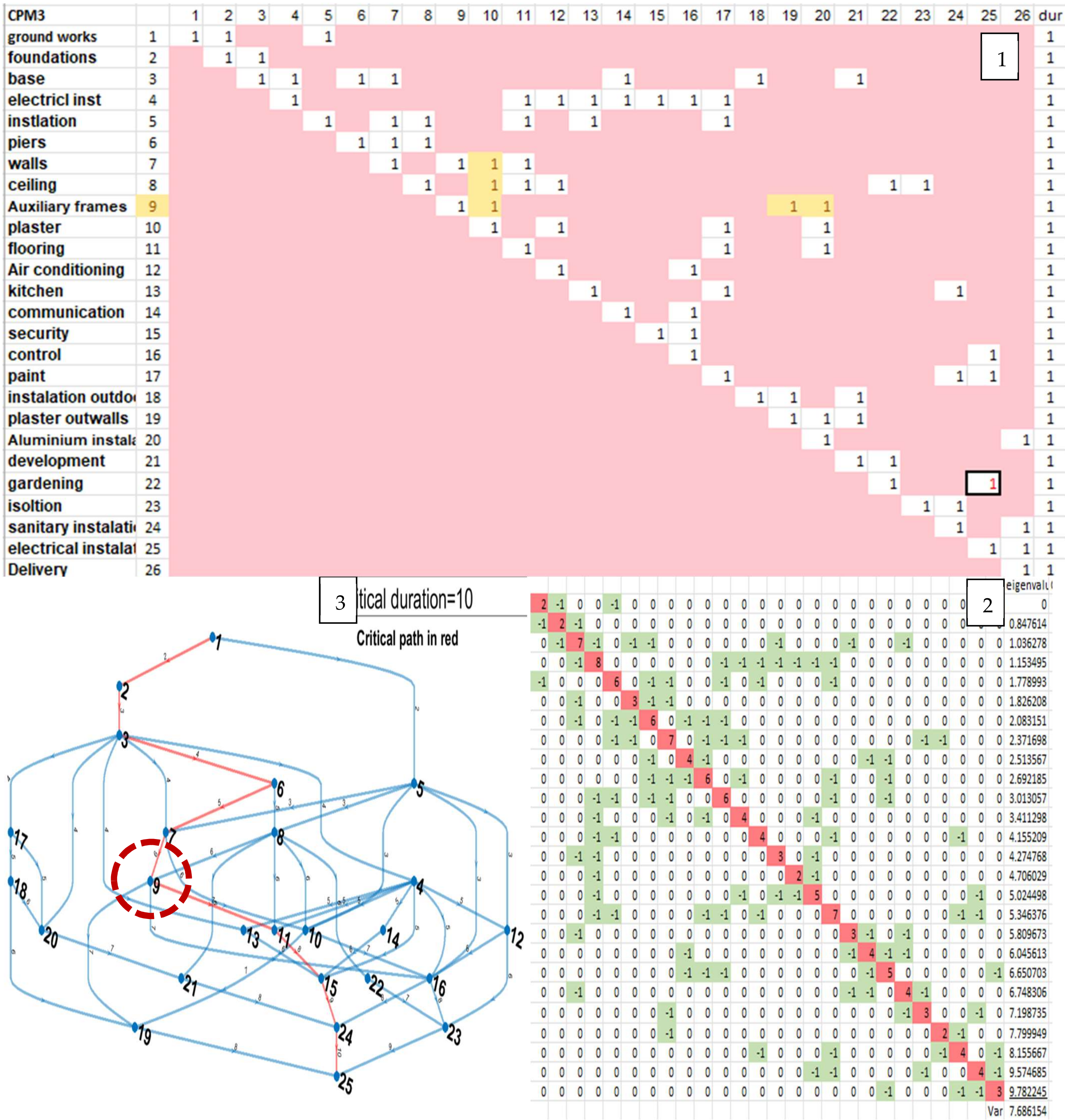


Figure 3. CPM3 Adj. Matrix (1) Laplacian(2) and network with location of added activity on the CP *(dashed circle)*.

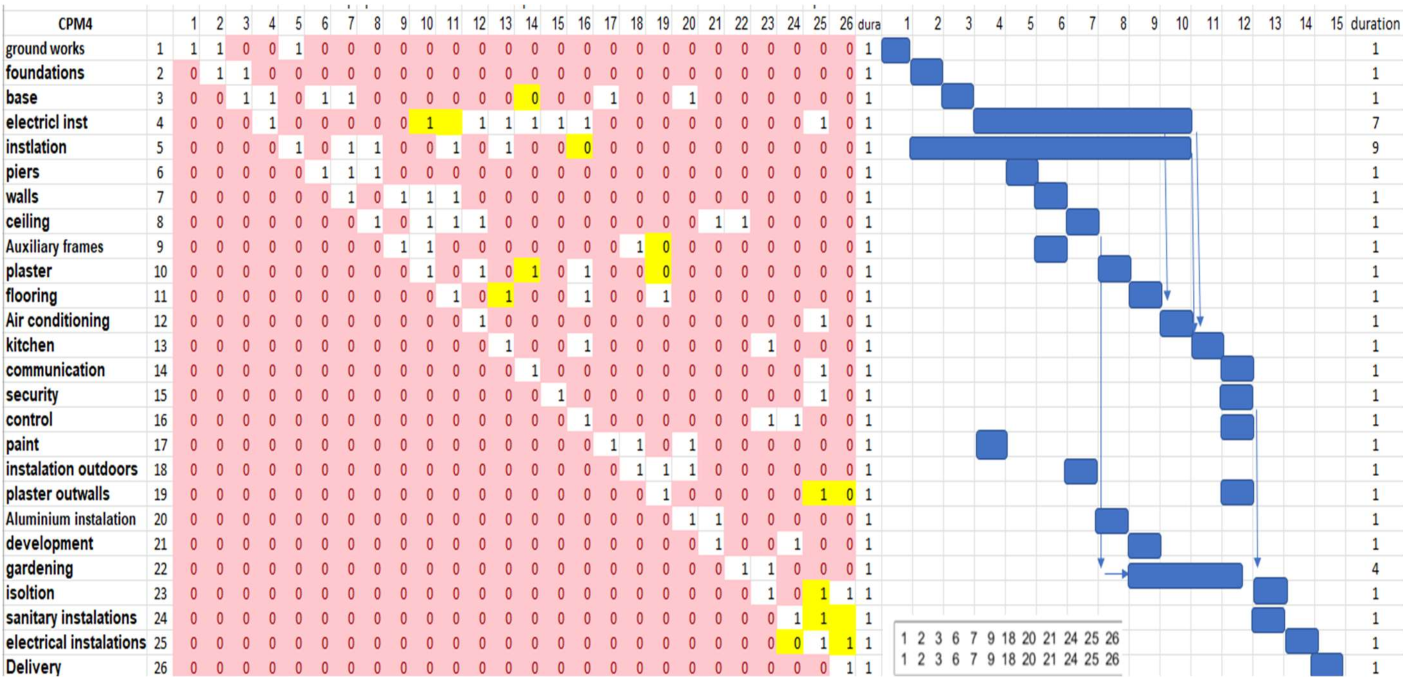


Figure 4. CPM4 Adj. Matrix and Gantt, changes highlighted in yellow.

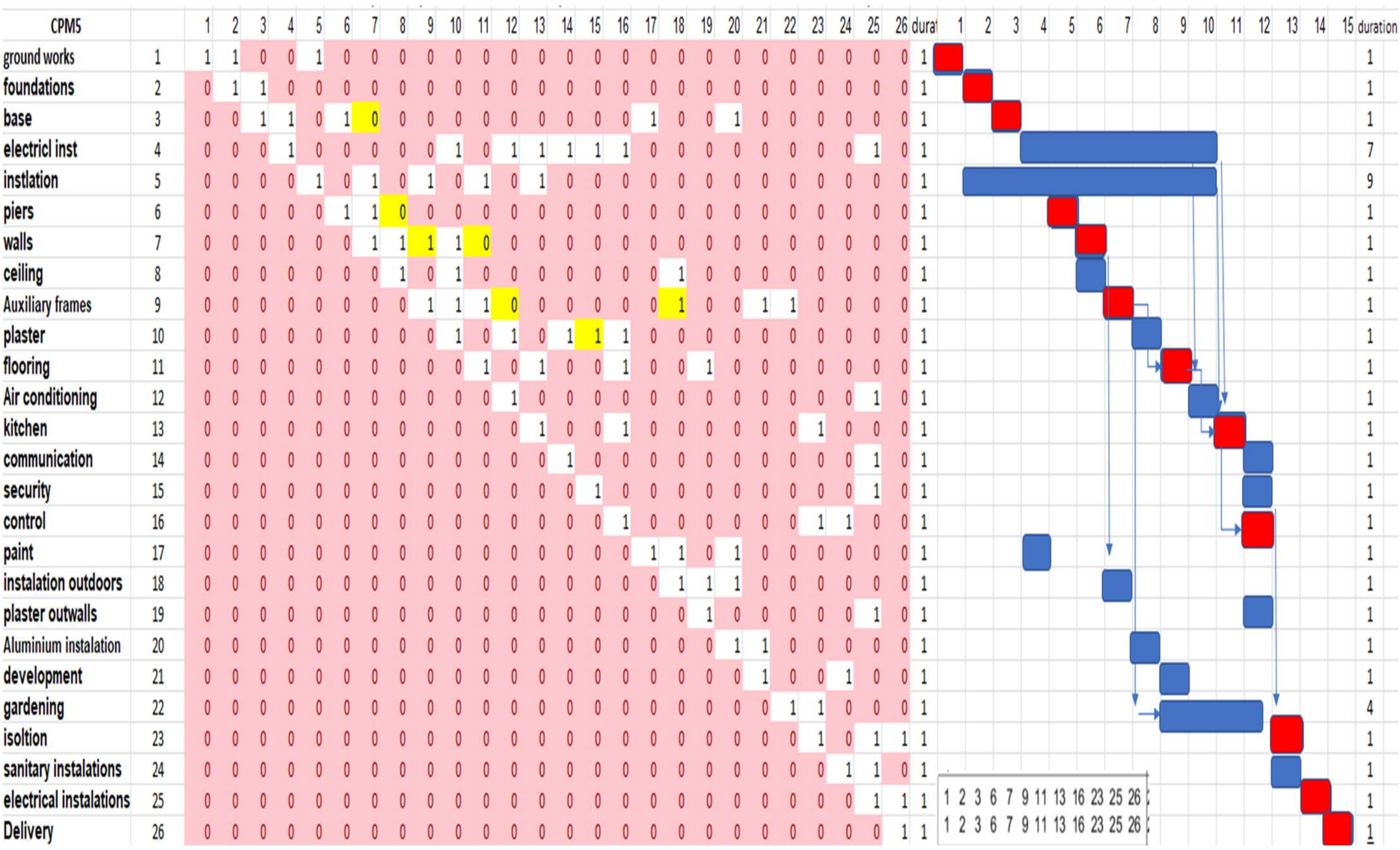


Figure 5. CPM5 Adj. Matrix, and Gantt with Critical Path, changes highlighted in yellow.

Decision rules: no correction for above threshold duration overflow faults, and correction of all below threshold duration overflow faults. Decision thresholds: t>1, t>0.55, t>0.05. All faults of magnitude sub-threshold are truncated. The decision rules are equated with quality; when all other parameters are equal, a higher threshold represents a higher quality.

The two **PDF** used for the experiments are presented in Figure 6, they are: LN(1.15,0.99) which befits construction projects (such as case-studies 1-4), and LN(2,0.33) that is fitted from an infrastructure system database.

Faults Power functions generated for each distribution are presented in Figure 6 with respective colors; in black the power function that was used; this power function is appropriate for well-managed projects. For in depth analysis of this function, origin, and traits please refer to [12].

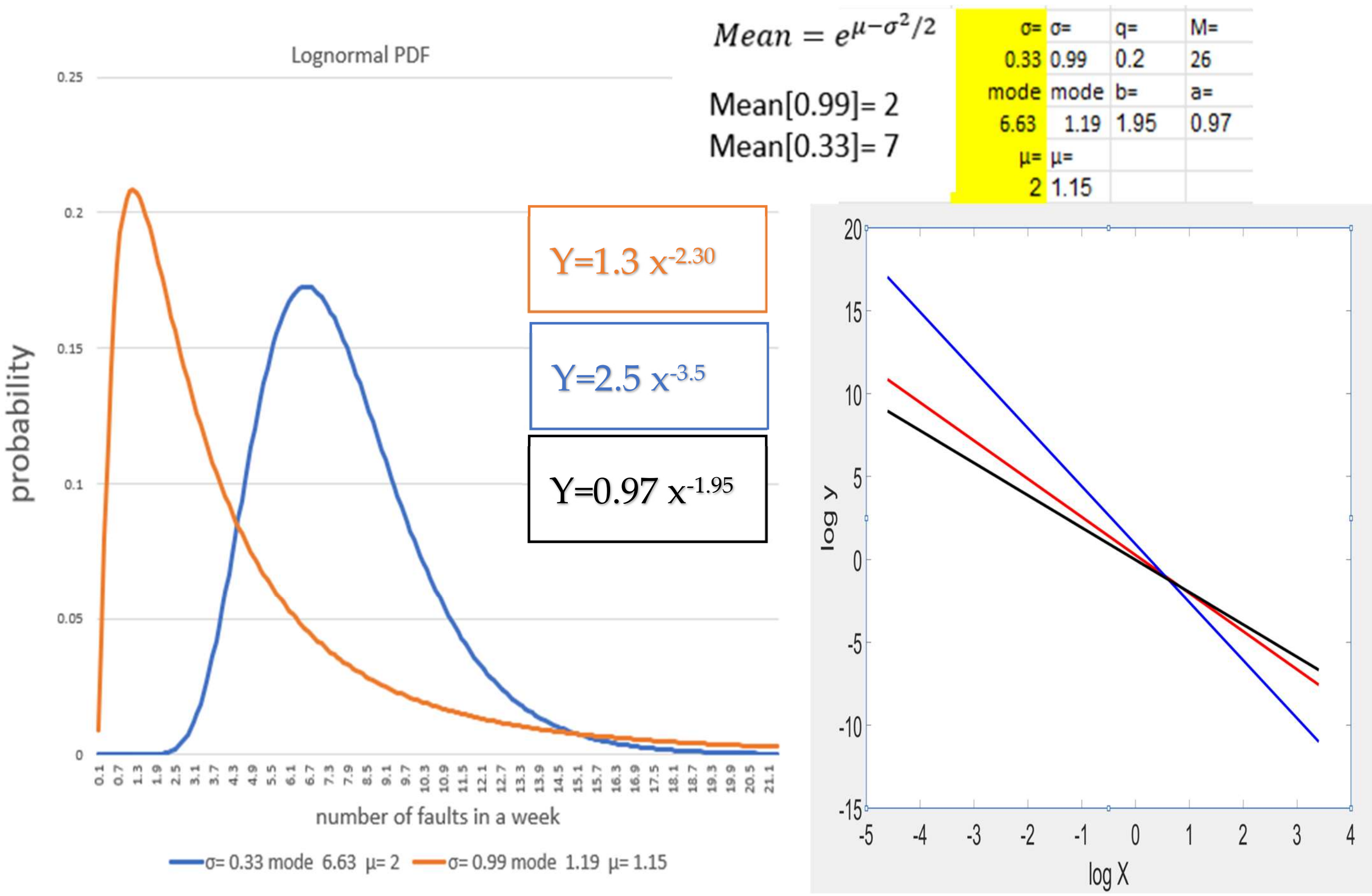


Figure 6. Statistics and parameters of Faults PDF, power function is calculated per Yonat *et al.* (2023) [12].

5.2. Experiments' Results

5.2.1 Observations:

Edges. The max number of edges for an 'n' nodes nondirected complete graph network is given by n×(n−1). For CPM3 through CPM5, this results in 650 possible edges (Table 2). In contrast, the actual number of edges used in CPM1 through CPM5 is less than 9% of this total.

Critical Path (CP) lengths and alternative CPs progressively accumulate (Table 3) as the system transitions from CPM1 to CPM5.

Outdegree diagrams show power function degree distribution (Figure 7.2, Figure 8.2, and Figure 9.2). Downstream outdegree propagation modes (Figure 7.1, Figure 8.1, Figure 9.1) suggest repetitive formations. Free Fourier Transform (fft) of the outdegree vector of Figure 7.1 confirms this suggestion (Figure 7.3).

Degree Power functions were fitted by Matlab Curve fitter app. to outdegree distribution (likelihood) of all experiments and case-studies with confidence margins of 95% (Figure 7, Figure 8, Figure 9, Figure 17), confirming that all the networks are scale free.

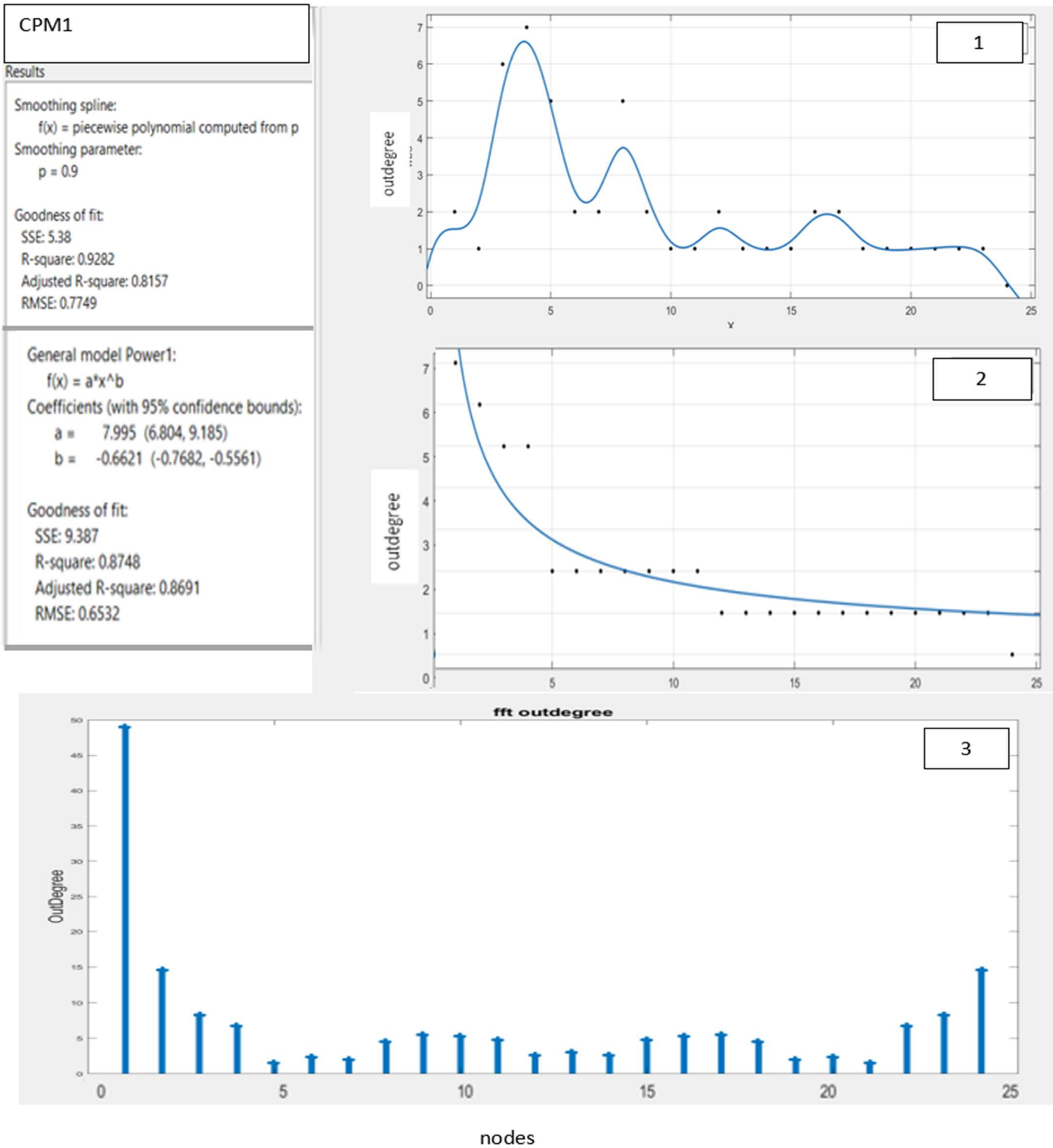


Figure 7. CPM1 Outdegree distribution vs. node numbers (1), outdegree magnitude PDF (2), fft(outdegree)(3).

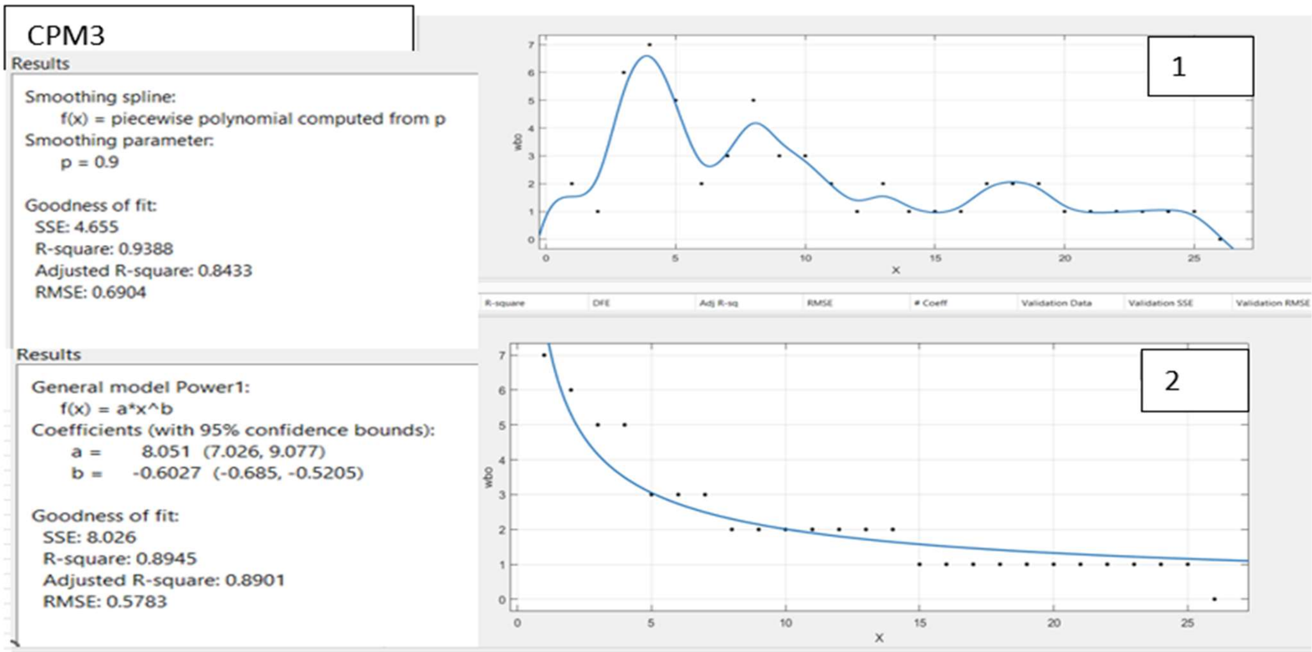


Figure *8.* CPM3 nodes Outdegree distribution graph and power function.

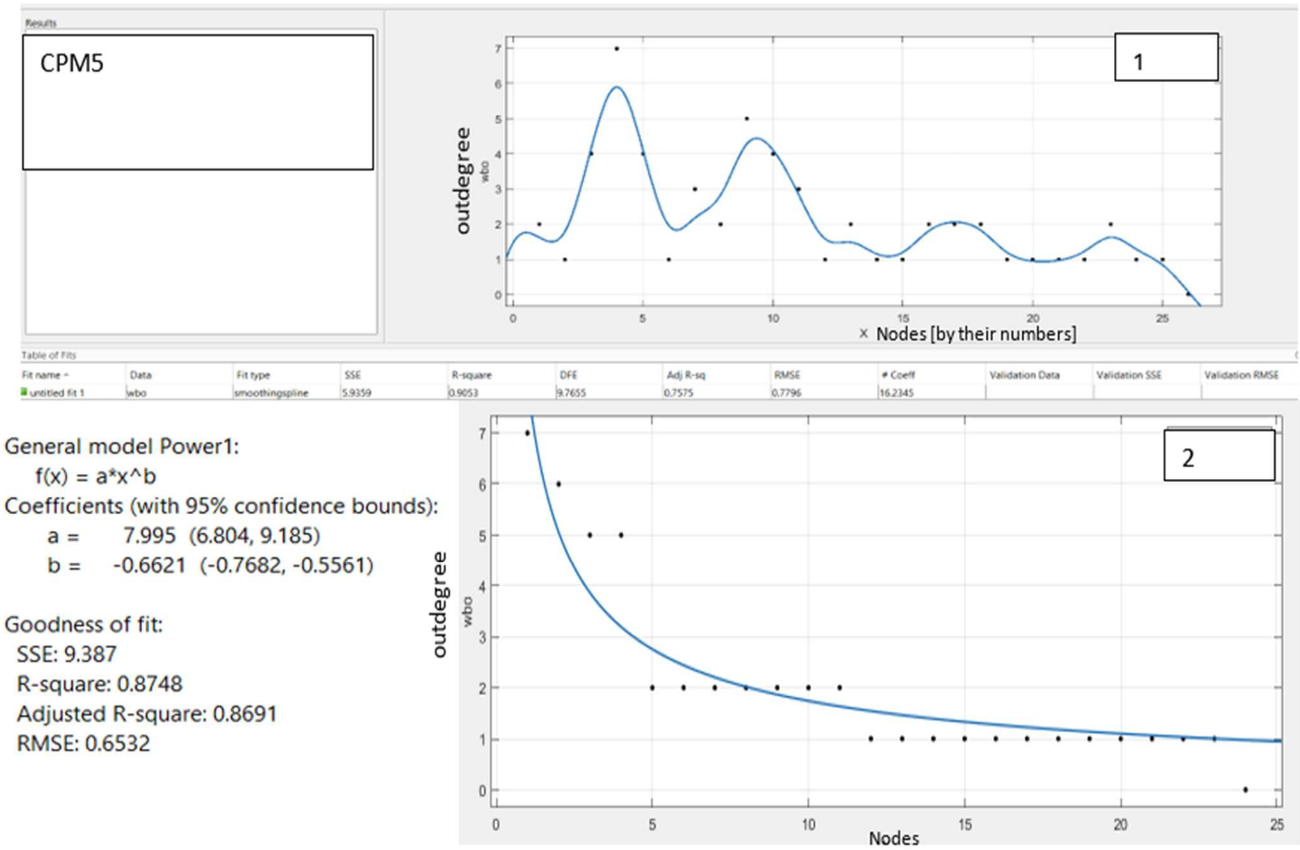


Figure 9. CPM5 (1) Outdegree distribution graph and (2) their power function magnitude distribution.

5.2.2 Explicatory Parameters

Table 2. Explicatory parameters.

#	CPM1	CPM2	CPM3	CPM4	CPM5
Number of Nodes	24	25	26	26	26
Trace (Laplacian)	98	106	114	112	110
Number of edges	49	53	57	56	55
n*(n-1)	552	600	650	650	650
Mean Degree	4.08	4.24	4.38	4.31	4.23
Maximum Degree	8.00	8.00	8.00	8.00	8.00
min span tree	5	5	5	4	4
all span trees	53	66	87	134	124
average spa tree	7.60	7.45	7.76	8.45	8.47
R^2	0.875	0.887	0.895	0.916	0.875
'b'	0.662	0.630	0.603	0.585	0.662
Entropy σ=.33	0.1414	0.3251	0.3251	0.3258	0.3251
Entropy σ=.99	1.2162	2.1965	2.1965	1.7268	1.7268
Ntropy σ=.33	0.204	0.469	0.469	0.470	0.469
Ntropy σ=.99	0.679	0.954	0.954	0.8874	0.8874
Laplacian Variance (σ_μ^2)	0.463	0.418	0.400	0.443	0.457
eigen ratio	16.04	11.62	11.54	13.45	14.41
Var(eigenvalues)	7.72	7.52	7.69	8.22	8.18
Var(Laplacian)			27.68		26.80

Table 3. Number of paths for Max-span-trees.

Maxspantree length	12	11	10	9	8	7	6	5
CPM1			2	11	16	15	6	3
CPM2			2	11	20	19	10	4
CPM3		2	6	17	25	22	11	4
CPM4	1	7	22	35	35	25	8	1
CPM5	4	8	22	21	31	30	7	1

The power parameter 'b' is not correlated with average Degree and the number of possible paths (all-span trees) (Table 2). The expectation that **b** would be positively correlated with graph diameter was not vindicated owing to small-world effect.

R^2 is a measure for the goodness of fit to a power function estimate. R^2 produces high results for power functions and exponentials. R^2 is biased by the magnitude of the extreme events being (sometimes arbitrarily or randomly) presented in the power function thus limiting its relevance.

Spanning trees for 'n' nodes graph, the maximum number of is n^(n-2) (Cayley's formula); for CPM1 this number is in the magnitude of 10^{30} and for CPM2 ~10^{32}. Yet the number of max-span-trees were ~10^2 at most.

Addition of one activity (CPM2 and CPM3) added 13, 21 possible paths respectively (out of added ~10^{32}, ~10^{34} possibilities respectively), whereas in CPM4, adjusting 7 and deleting one edge added 47 possible paths and the tuning to the expert's CP by deleting an edge and relocating three edges in CPM5 subtracted 10 possible paths.

Stdv: The calculated critical path for CPM2 is given in Figure 2.3, for CPM3 Figure 3.3. and CPM5 in Figure 5.

Submitting CPM3 to the higher Stdv PDF (Figure 10) results in a collapse of stability. The energy of the high Stdv faults, threw all CPM1 to CPM 5 networks out of the CP for all iteration modes (Figure 11 for CPM 1, Figure 12 for CPM 2,3,4,5).

Criticality Index varied with iterations (Figure 11), with Stdv (Figure 10 vs. Figure 13.1), with decision rules (Figure 14), and even for different runs (Figure 10 and Figure 12.2, Figure 11). New paths were found (Figure 10).

Morphology: For the different CPM small morphological variation produced extensive changes (Figure 12).

Entropy changed with iterations going to ever higher values (Figure 13). Entropy changed on different runs for the same number of iterations, such as in Figure 12.2 vs. Figure 10; and for different decision rules Figure 13 vs. Figure 10.

Ntropy: Where Ntropy goes to 1 entropy is maximized, the probability of all CP equalizes.

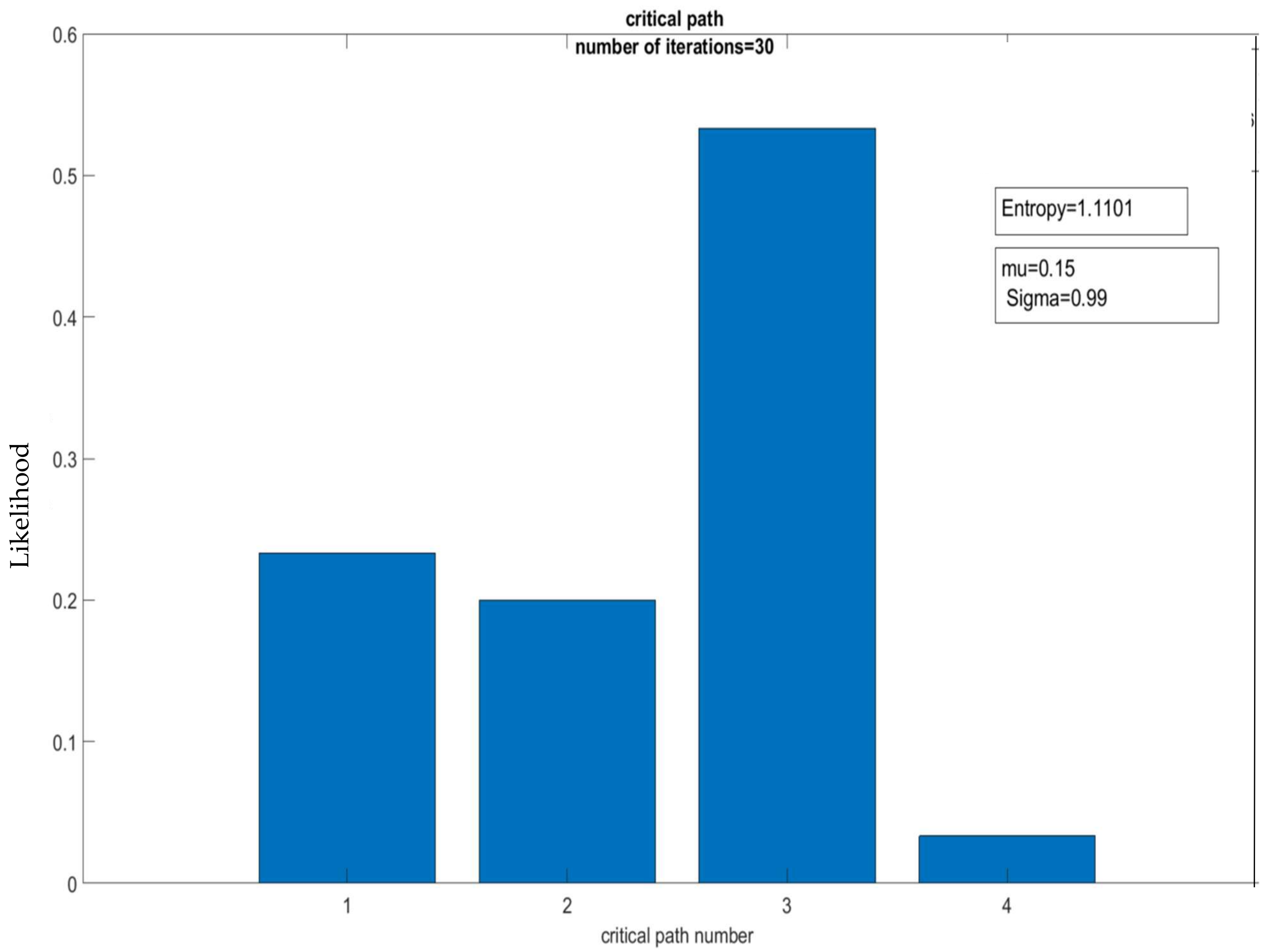


Figure 10. CPM3 CP changes 30 iterations LN (0.15,0.99), t>1.

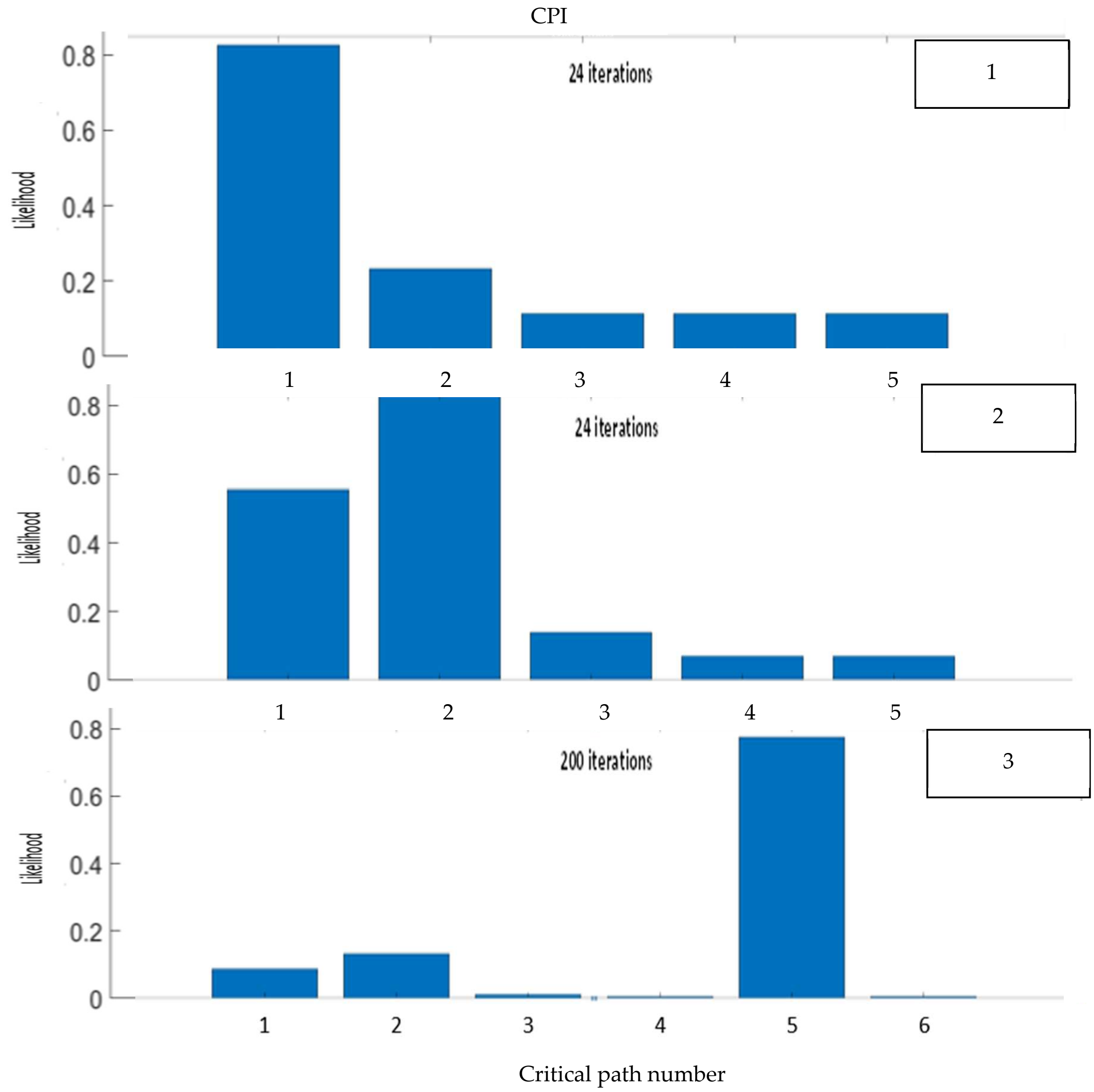


Figure 11. CPM1 Criticality Index variations with iterations. Abscise are the different CI.

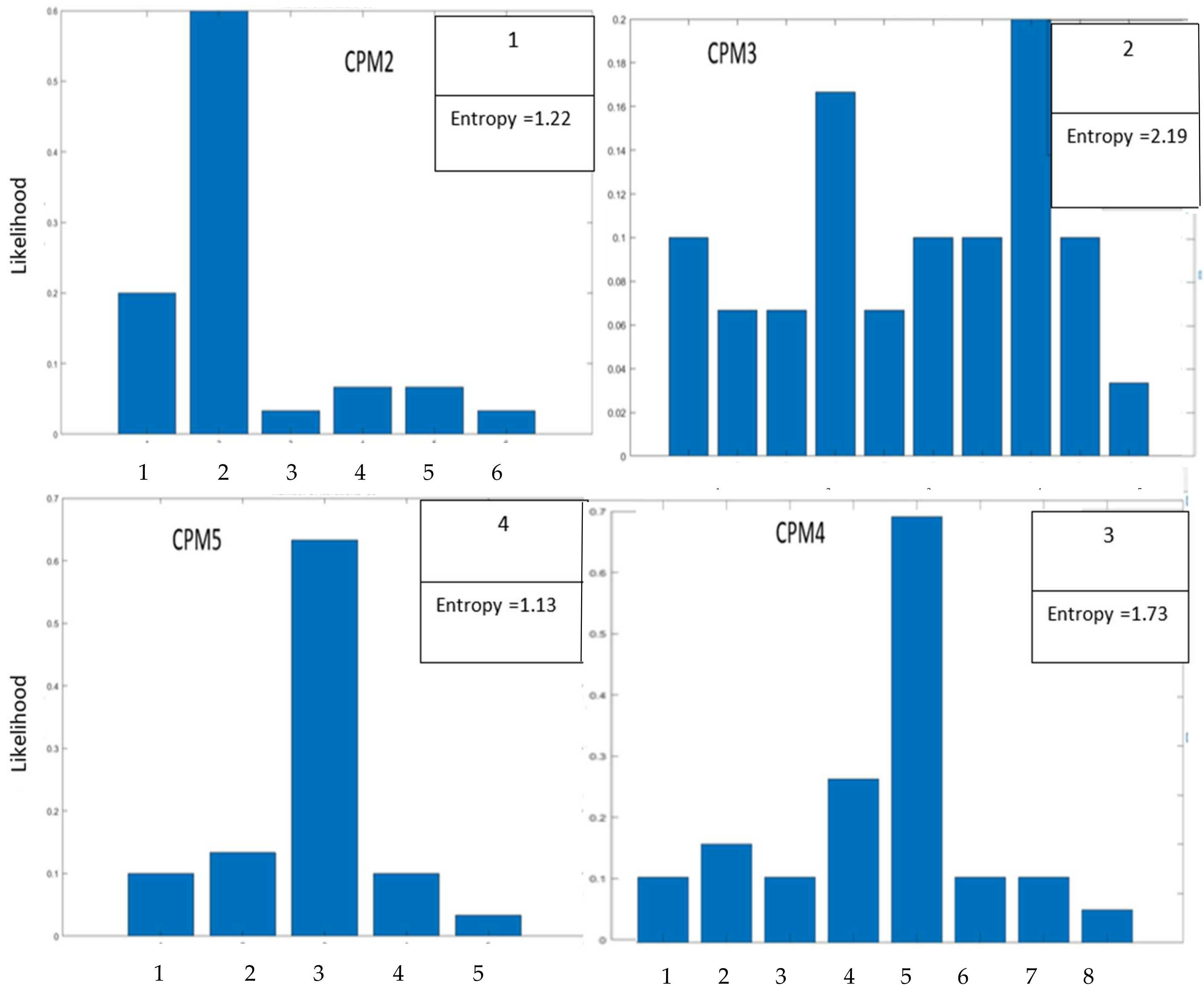


Figure 12. CI for systems CPM2,…,5 after 30 iterations, *LN (0.15,0.99)*.

Attractors

Table 3 lists all Max span trees for CPM1 through CPM5. In CPM Max-span trees are calculated before work commencement, the longest span tree is referred to as '**baseline'** Critical Paths (CPs) and on event of alternative CP (such are three 12 edges paths in CPM5) they are referred to as "alternative CPs". Baseline CPs often correspond to attractors, most notably for the lower standard deviation (Figure 13). In Figure 13.1 CPM3 shows two CPs having equal likelihood and corresponding with the baseline CPs. In Figure 13 CPM5 repeatedly selects three out of four baseline CPs. Figure 14 present two runs of 30 iterations of the lower Stdv PDF; the two runs exhibited a tendency towards one of the max-span-trees, the actual max CPI path was randomly selected by the algorithm; the lower quality rule had an effect of exploration. Figure 12 shows that high Stdv systems energy may throw the system out of the attractors, new CP are formed, not necessarily in a max-span-tree. Figure 14 shows that with t>1 rule and the lower Stdv the system preferred one of the max-span-trees of CPM5, in the iteration shown on Figure 14.1, the system stayed within it most of the time, while for CPM3 Figure 10, it chose for t>1 a short path as an attractor. Considering its relative entropy, CPM5 demonstrates greater stability. Figure 12.4 shows that CPM5 has a lower entropy compared to other models, indicating a more stable configuration.

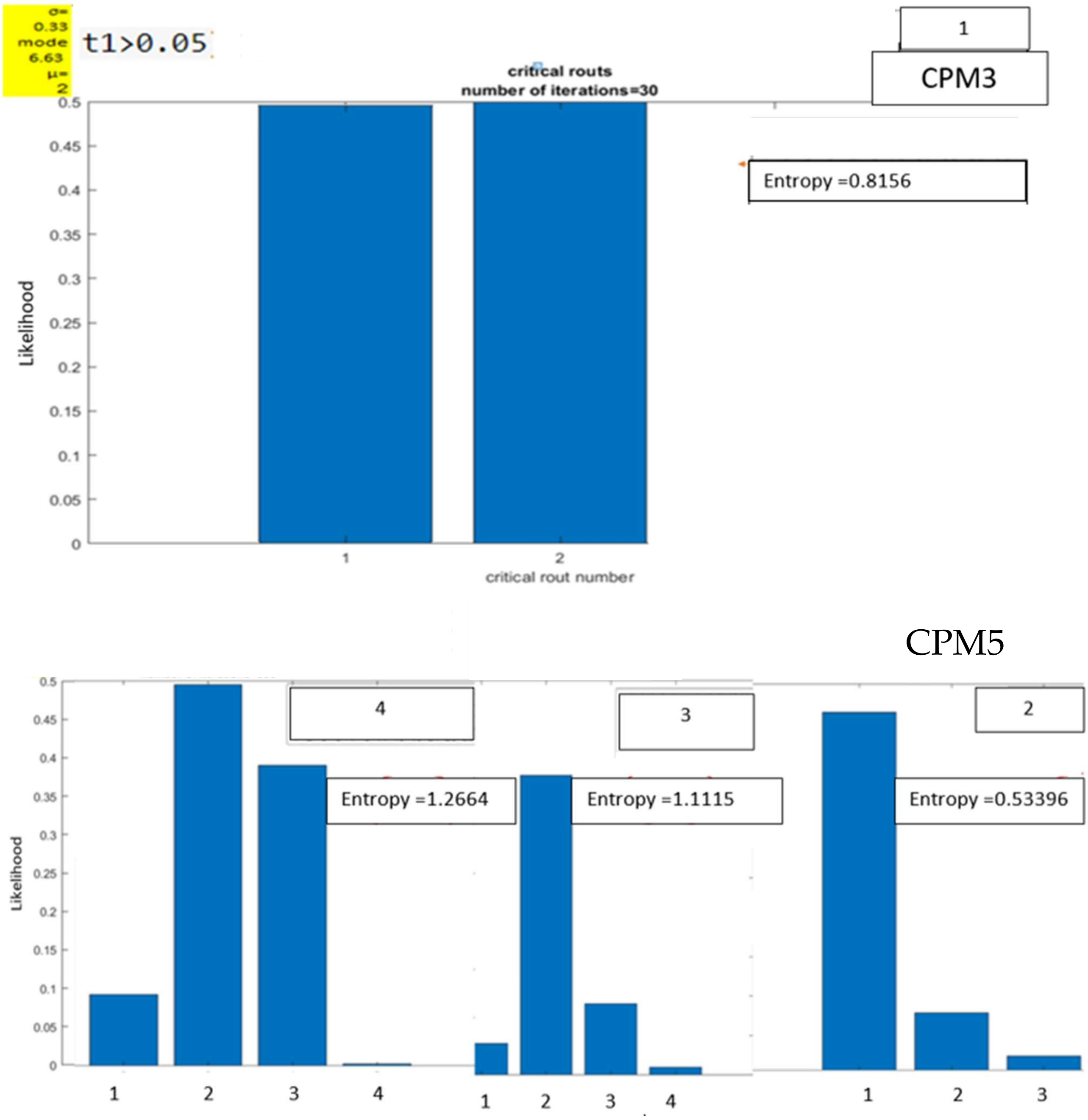


Figure 13. CPM 3 σ=0.33 attractor, 30 iterations (1), CPM5 CPI for 30 (2), 100 (3), 500 (4) iterations, t>0.05.

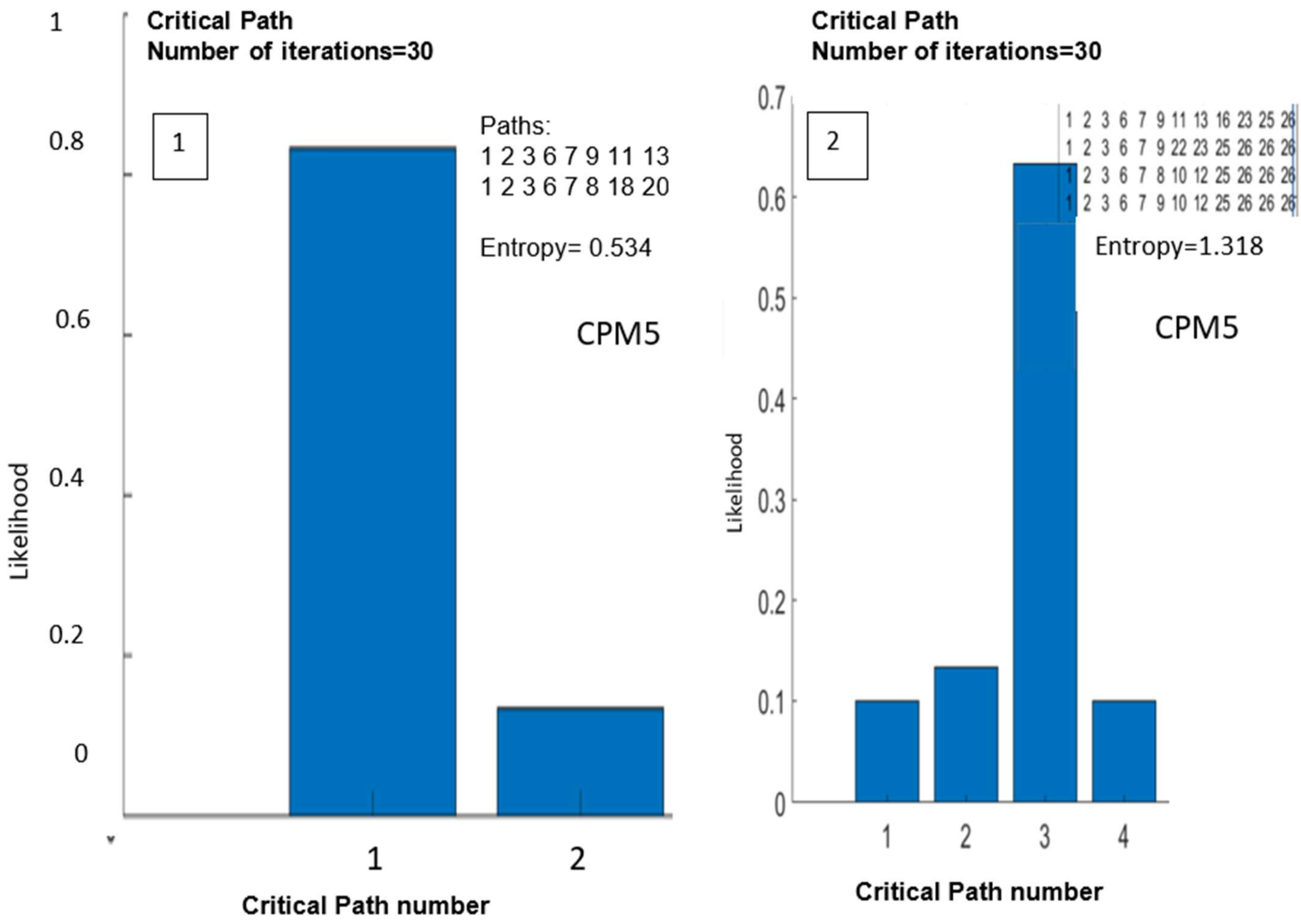


Figure 14. Robustness of attractors for CPM5 LN (2,.33), t>1 (1), t>0.55 (2).

Eigenvectors: Figure 15 may direct to modes of vibrations that elected the higher nodes in the eigenvectors, indicating that the attractors are more likely nodes than paths. The refraction modes of Figure 15 for CPM5 are inverse to those of CPM3 and CPM4. The refraction of CPM5 has zero energy at the end-nodes. We recall that CPM 5 is an expert's choice of structuring a network with more alternative CPs and longer paths.

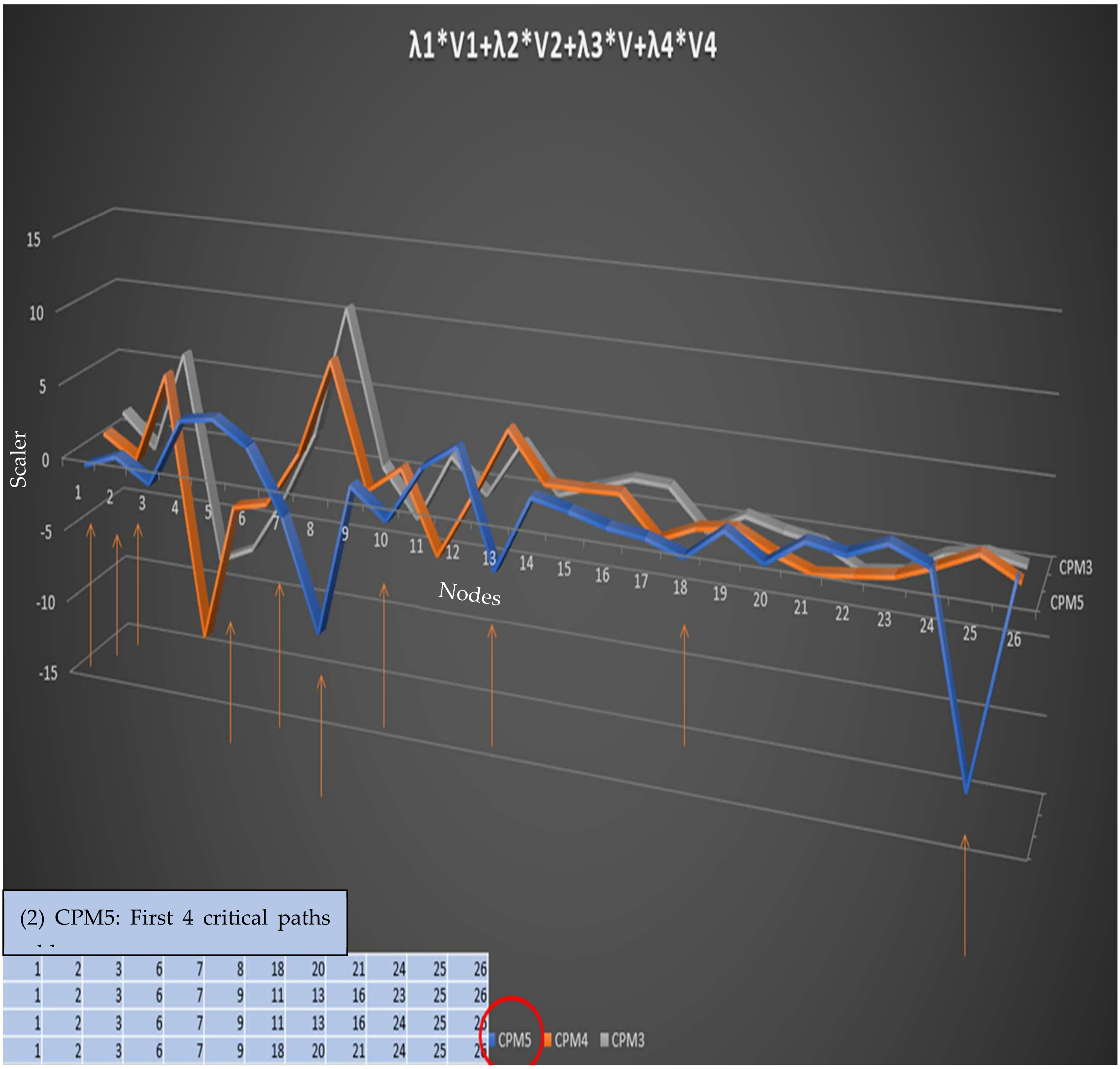
The spectral clustering analysis suggests that CPM5 has better clustering characteristics, thereby incorporating clustering as an additional explicatory parameter (Figure 16). In Figure 16 both CPM3 and CPM5 CPs are associated with the central cluster. However, CPM5 exhibits a higher clustering coefficient compared to CPM3, indicating clearer alignment and greater cohesion within the network. This is an interesting finding that portrays the improved coherence and synchronization of CPM5 planning as reflected in its network morphology. The lower entropies of CPM4 and CPM5 in Figure 12 attest to this.

The explanation is in joint and conditional entropies:

$$H(X,Y) = -\sum_{i=1}^{n}\sum_{j=1}^{m} p(x_i, y_j)\, log\,(p(x_i, y_j)) \qquad (11$$

(Karmeshu, 2003)

As the mutual probability p(x,y) is higher, entropy drops.



1	2	3	6	7	8	18	20	21	24	25	26
1	2	3	6	7	9	11	13	16	23	25	26
1	2	3	6	7	9	11	13	16	24	25	26
1	2	3	6	7	9	18	20	21	24	25	26

Figure 15. First 4 eigenvectors refraction mode for CPM3,..,5, graph spectrum. (2) the first 4 CP for CPM5.

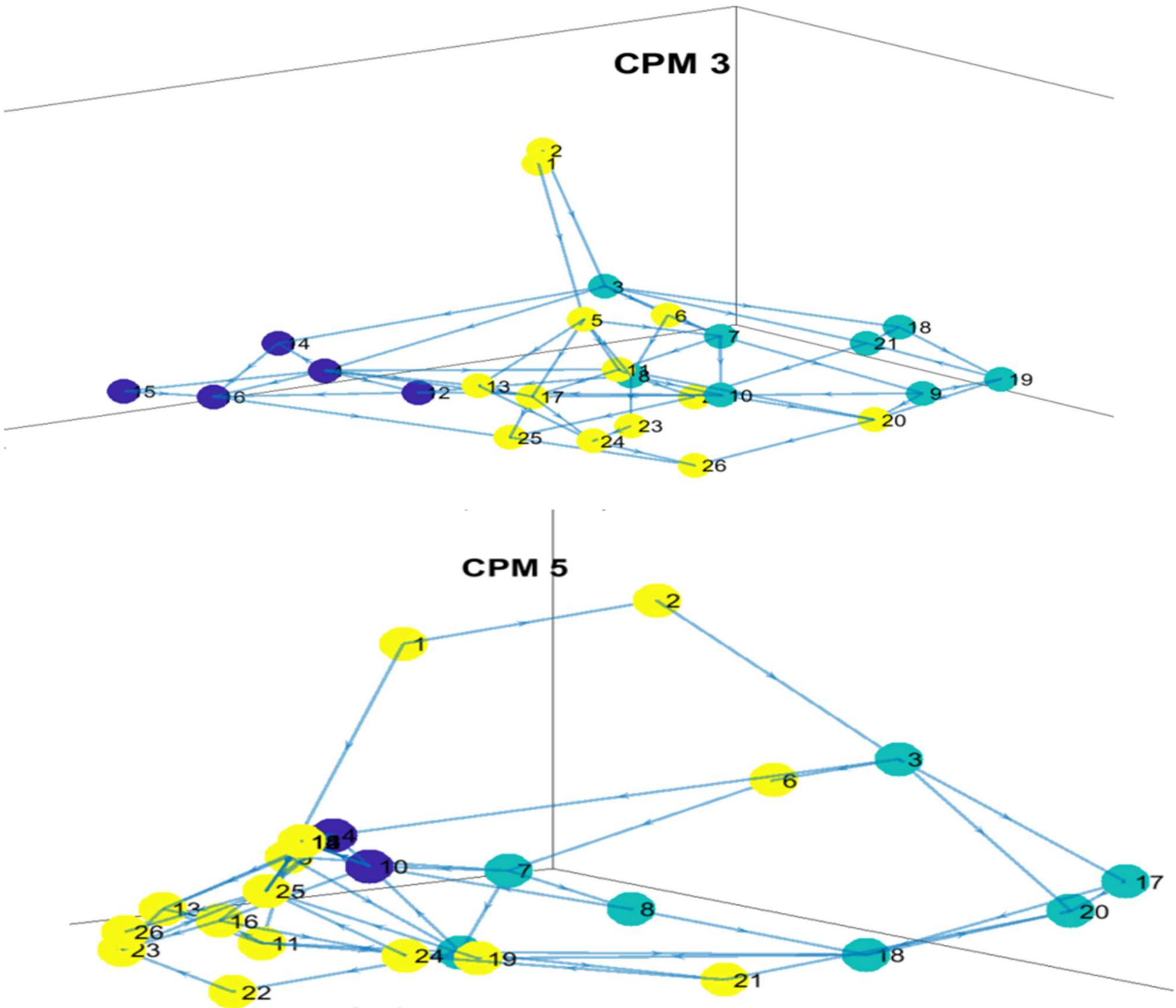


Figure 16. Three D eigenvector space spectral clustering CPM-3, CPM5. Node clustering by color.

5.3. Case-Studies

Case Study 1 C2012-13 Pumping Station involves a short project timeline with only 28 entries. Despite this, there was a major collapse of the Critical Path (CP).

Case Study 2 C2011-13 Wind Farm features a network with 166 nodes and 120 documented time intervals. Although the network degree is low and the project exemplifies concurrent engineering, with numerous large buffers supporting the designated CP, the CP still collapsed.

Case Study 3 C2011-10 concurrent construction is a model of good practice. It was a well-planned and managed, in-situ synchronized, mostly linear production, there was no imported risk, ample buffers on non-critical paths, and a short timeline. Despite the negligible time overflow, the CP collapsed.

Case Study 4 Pre-cast schedule presents a DSM of 16 hammock activities, yet the outdegree magnitude fitted power function reveals network complexity. Despite being a small, rudimentary system, the CP still collapsed.

DSM matrices were generated for all case studies, along with Laplacian matrices, outdegree distribution Power functions, Principal Component Analysis, and descriptive statistics.

5.4. Case Study Results

5.4.1. Imported Risk-Case Study 1.

Figure 17 provides a snapshot of one of the divergences of Case Study 1 network from CP.

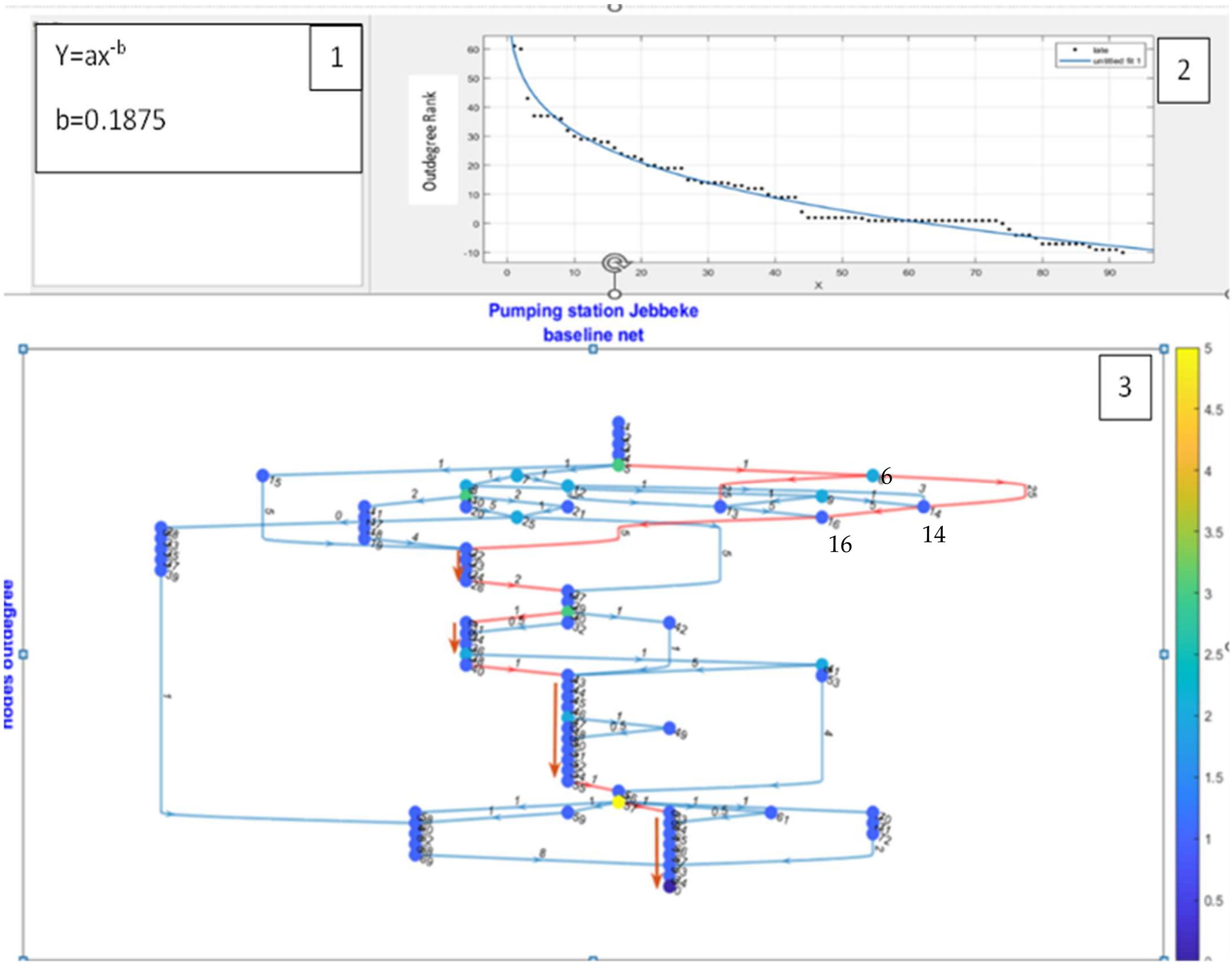


Figure 17. Pumping station power function (1); Outdegree distribution (2); CP deviations (3).

Figure 18.1 illustrates that despite the absence of activity duration overflows, activities still experienced delays. Figure 18.2 shows a spike in costs, which exhibited no correlation with Figure 18.1 time-overflows. Both effects are attributed to imported risk.

Figure.2 shows that cost spikes are independent of production and of imported risk, exemplifying the sociological phenomena of power plays [12], there are a plethora of other influences in the sociological category for example delays in payments [26], and contract mismanagement [27]; all are exogenic to CPM systems, and therefore, unaccountable.

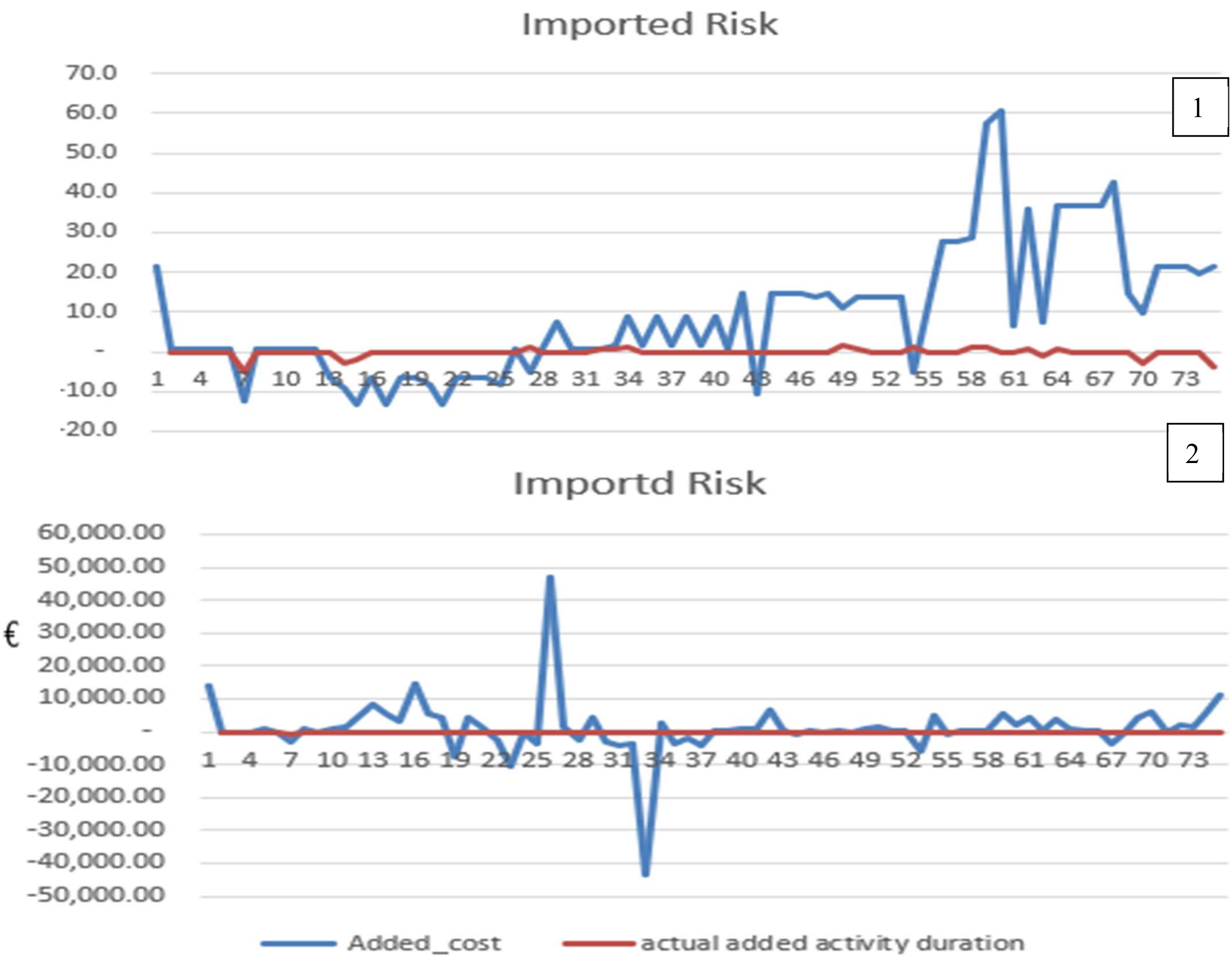


Figure 18. Presentation of Imported risk by latencies (1) and cost (2). X-tick values are discrete time units in weeks.

5.4.2. Synchronization- Case Study 2.

Figure 19.1 baseline CP hints to an ergodic function space for the actual CP path. Synchronized-concurrent activities are attractors (Figure 19.2). It is important to note that the actual timeline did not collapse, only the CPM prediction and stability collapsed. The success of practice here is attributed to buffers and early time ('et') management; attesting to time management practice where potentiality coexists with actuality.

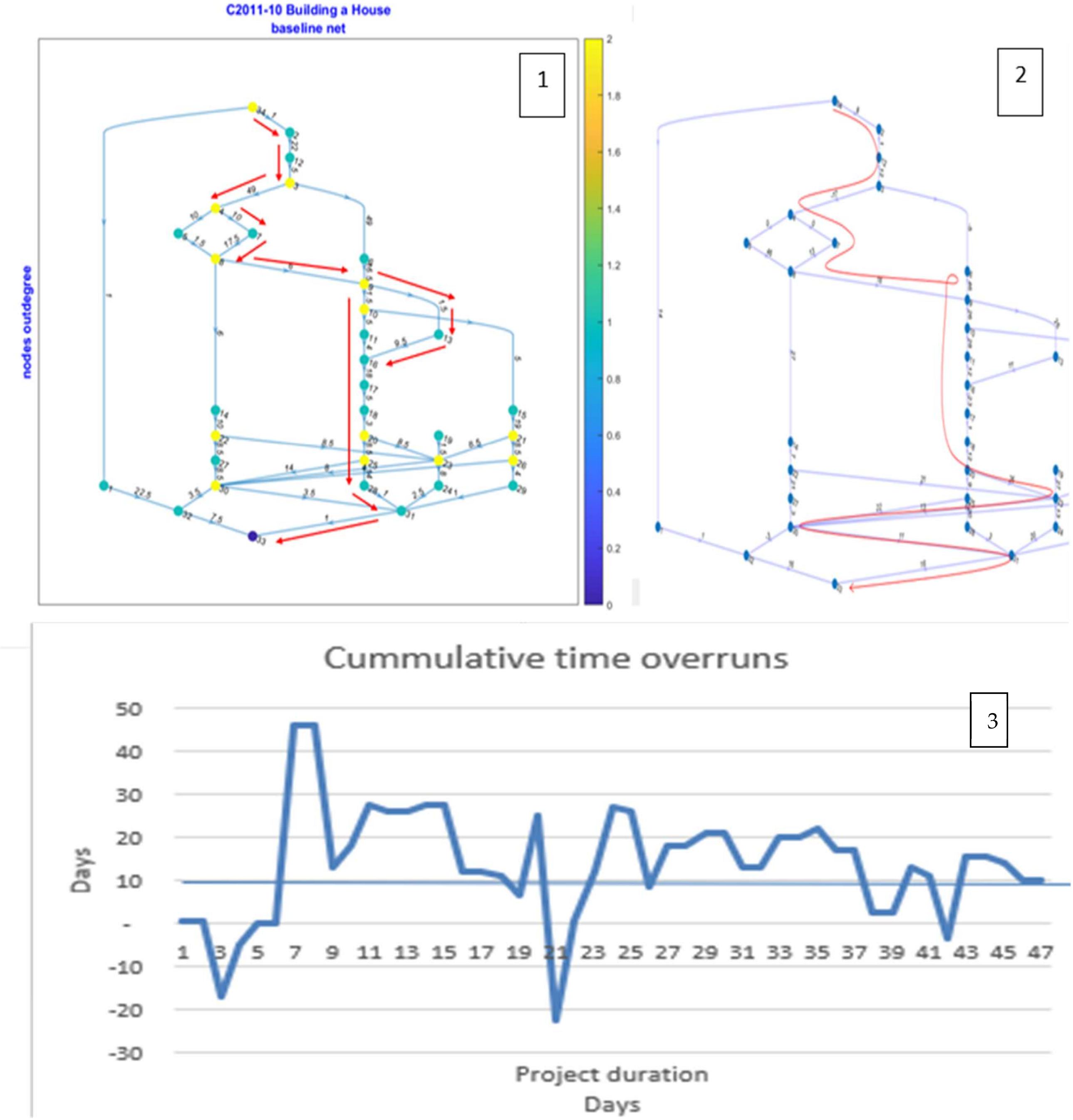


Figure 19. CP planned (1); CP actual (2) showing synchronization; Latency graph (3).

5.4.3. Reification - Case Study 3

The baseline CP is portrayed in (Figure 20.1).

CPM CP collapsed (Figure 20.3) while the project was not affected (Figure 20.4).

It is notable that the planned/expected dates, durations, and even the sequences were not met, almost as a rule. The CPM model had no predictive value.

Figure 21 nodes 8,9,23 and 30 are highlighted in Figure 21.1, these nodes are within a sequential concurrent sequence, the nodes bear no added impact in relation to the other nodes in that sequence,- PCA minima shown with red arrows on Figure 21 have no justification.

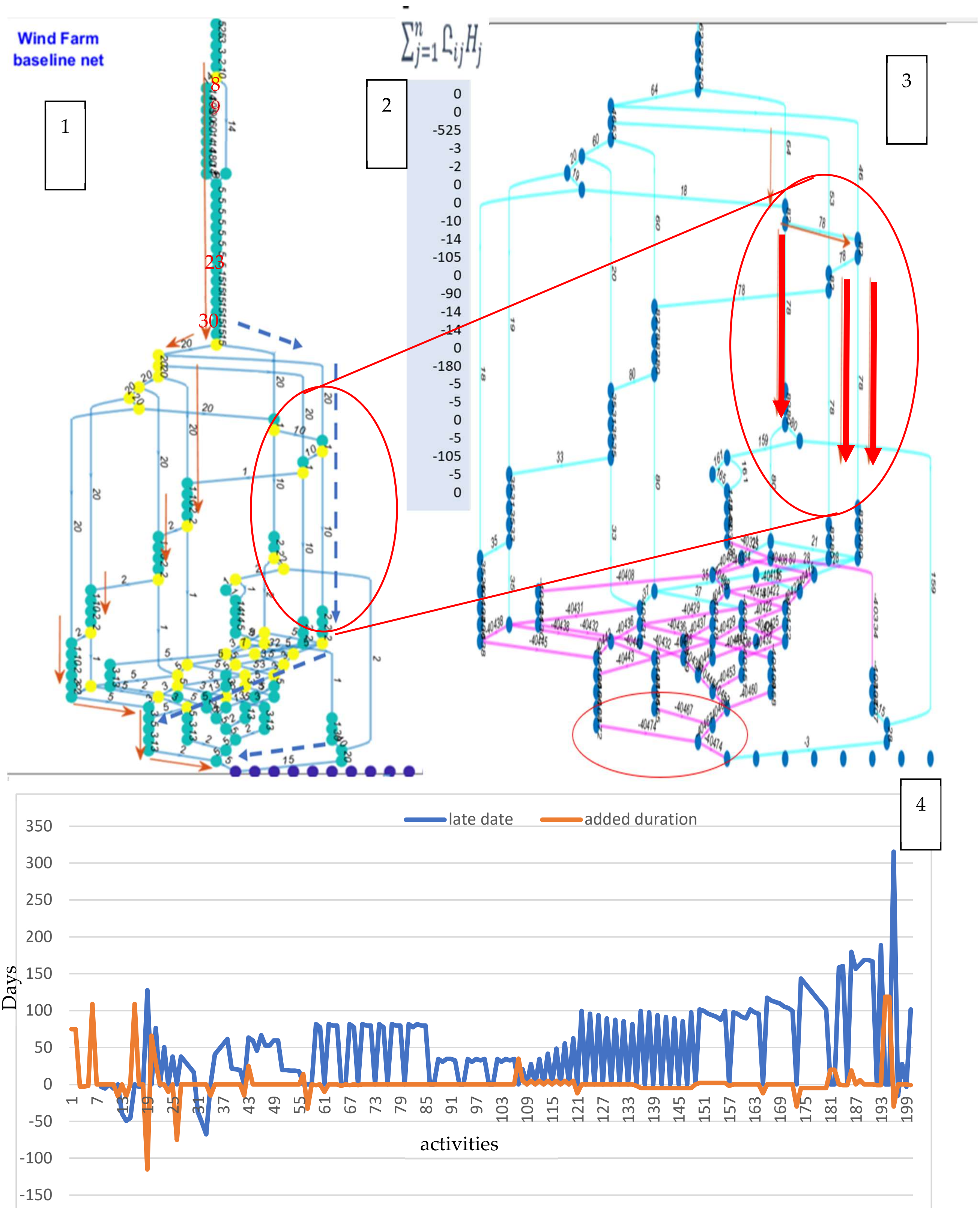


Figure 20. Case Study 3 CP (1), $\sum_{j=1}^{n} \mathfrak{L}_{ij}H_j$ (2) actual path (3), actual duration overflow per activity (4) in blue, the influence on the project latency in red.

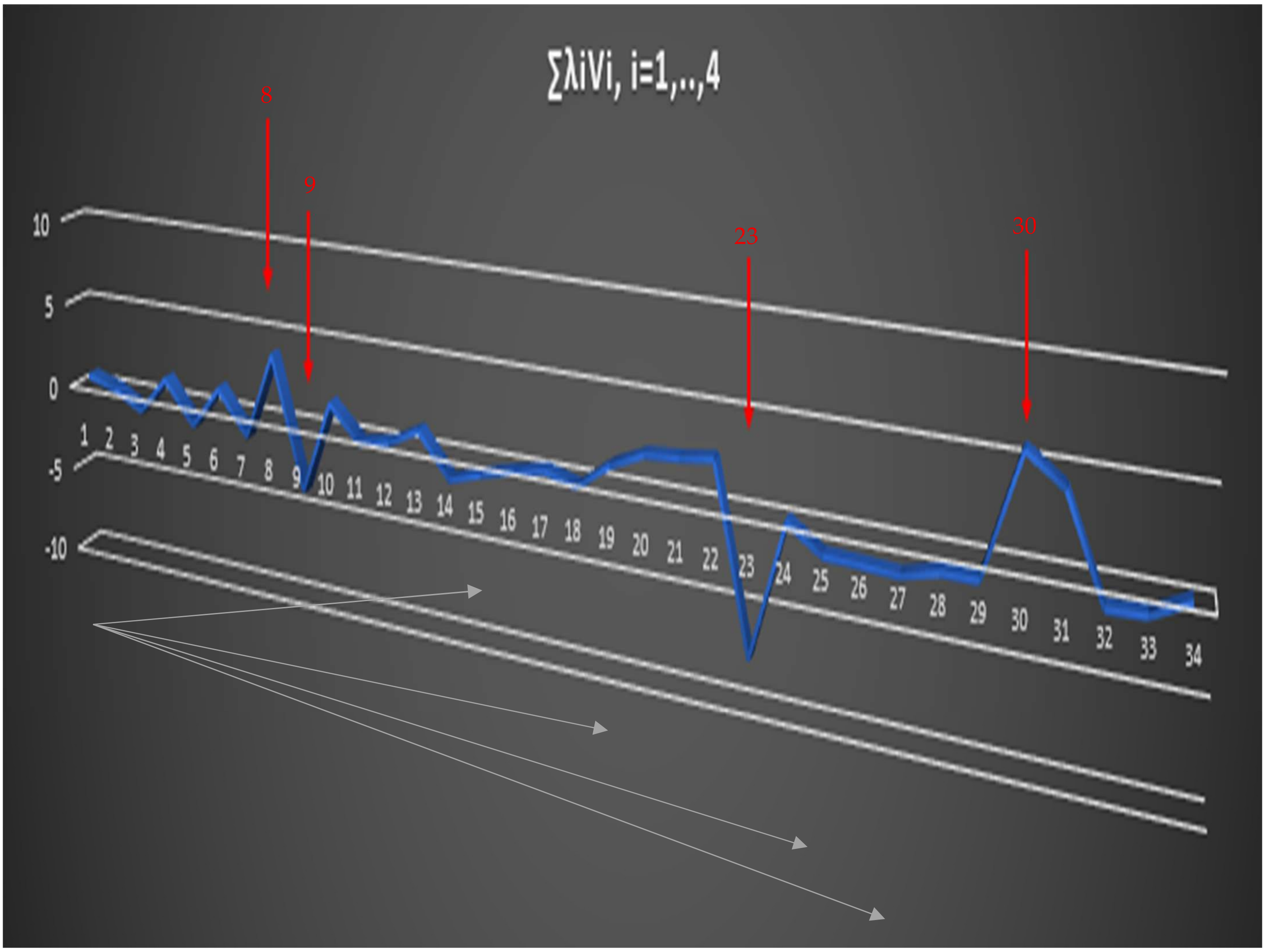


Figure 21. PCA analysis for Case Study 3.

5.4.4. Coupled Activities- Case Study 4.

The network in Figure 22 displays numerous rework loops of varying orders, including 2nd, 3rd, 4th, and 5th orders, such as 'a4'-'a5'-'a4','a13'-'a15'-'a14'-'a13', a5'-'a10'-'a13'-'a15'-'a5'. Some of these loops do not reflect physical relationships but rather should be interpreted as information links. Additionally, Figure 22 demonstrates higher orders of coupling, with the E^4 Boolean cube of Figure 22.2 establishing that all activities from a4 to a15 are coupled to the fourth degree.

Shen et al. (2022) [6] idea was to rearrange the DSM in such a way that loops are avoided. This task was performed by adding activities whenever a loop was created on the initial DSM. This is a standard DSM solution intended to eliminate first order loops; in this case it was not successful, especially noteworthy is the neglect to address higher order loops.

There are conceptual limitations to hammock planning, for instance, 'a14' cast in situ precedes 'a12','a13' repetitively on all floors; the dependencies representation of concurrent hammocks is limited in CPM. It is safe to say that CPM does not adequately represent this project.

Pre-cast project original DSM

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16
a1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
a2	0		1	1	1											0
a3	0			1	1											0
a4	0				1	1	1			1	1	1	1	1	1	0
a5	0			1		1	1	1	1	1		1	1		1	0
a6	0				1		1									0
a7	0					1		1					1	1	1	1
a8	0								1				1			0
a9	0									1						0
a10	0												1	1		0
a11	0													1	1	1
a12	0												1	1	1	1
a13	0											1		1	1	1
a14	0												1		1	1
a15	0													1		1
a16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

1

No.	Task
a_1	Preplanning
a_2	Conceptual design
a_3	Preliminary design
a_4	Construction design
a_5	Component design
a_6	Material procurement
a_7	Component production
a_8	Stacking
a_9	Transportation
a_{10}	Site layout
a_{11}	Underground construction
a_{12}	Component positioning
a_{13}	Component installation
a_{14}	Cast-in-situ construction
a_{15}	Decoration and electromechanical engineering
a_{16}	Completion and acceptance

2

E1^4

	'a1'	'a2'	'a3'	'a4'	'a5'	'a6'	'a7'	'a8'	'a9'	'a10'	'a11'	'a12'	'a13'	'a14'	'a15'	'a16'
'a1'	-	-	-	97.61	121.75	73.77	117.67	97.19	58.75	63.55	30.13	117.31	208.74	208.45	230.97	177.73
'a2'	-	-	-	95.94	114.20	61.80	98.49	86.19	58.29	54.07	21.98	102.52	192.14	195.75	215.93	182.22
'a3'	-	-	-	83.51	94.66	45.92	76.65	61.39	51.14	43.76	18.08	83.90	151.52	148.84	168.81	149.57
'a4'	-	-	-	140.36	153.77	85.61	140.50	109.10	70.08	94.67	37.53	156.05	250.23	247.41	283.24	230.97
'a5'	-	-	-	121.16	159.00	77.48	129.23	87.89	70.24	84.65	44.40	142.47	236.60	241.67	261.09	217.47
'a6'	-	-	-	53.28	52.17	33.01	49.19	47.18	24.89	45.79	11.55	57.53	94.71	86.64	107.04	84.61
'a7'	-	-	-	60.32	75.08	38.58	65.97	48.11	38.14	35.29	17.76	68.26	126.68	135.31	131.76	110.66
'a8'	-	-	-	11.88	15.05	5.78	9.77	5.74	3.28	7.90	4.08	15.89	20.83	23.06	30.55	24.19
'a9'	-	-	-	10.34	10.84	3.71	6.87	2.63	2.11	3.71	2.94	9.44	13.17	17.46	14.94	16.61
'a10'	-	-	-	19.63	22.15	13.16	21.82	14.46	7.56	11.52	7.14	22.80	36.70	34.12	40.54	31.02
'a11'	-	-	-	18.70	22.05	14.00	22.03	17.82	8.40	11.28	5.97	21.58	39.29	38.82	43.31	33.53
'a12'	-	-	-	22.78	30.07	17.32	27.79	20.18	10.25	14.77	9.03	29.03	46.83	49.61	53.95	41.30
'a13'	-	-	-	46.56	51.02	29.29	47.49	37.86	22.31	26.08	11.95	49.88	87.34	86.25	97.31	80.13
'a14'	-	-	-	33.43	45.30	22.88	37.33	27.52	19.17	20.54	11.67	40.37	66.54	71.81	77.10	63.43
'a15'	-	-	-	51.47	54.65	28.47	47.23	38.39	28.94	26.73	10.55	50.88	92.68	88.12	102.09	88.84
'a16'	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Figure 22. Initial DSM with legend (1), E^4 Boolean matrix (2), network morphology with some higher order loops (3).

6. Falsification

Max Span-trees are ruled out because the system randomly selects critical paths from span-trees.

Max-span-trees (Table 2) relevance is incidental as the vibration modes CPI in Figure 10 show.

Degree by itself has no explicatory value (Table 3). When criticality index is decided by the initial paths, higher centrality may indicate better chance of correlation with CP.

Clustering coefficient has no explicatory value, missing implication of bridge activities, hammocks, number of nodes, coupling, and graph dimeter.

CI is ruled out because CI changes on iterations (Figure 11).

Power function 'b'

'b' is a phase parameter. In CPM1 'b' is equal to 'b' for CPM5, therefore 'b' must be rejected. 'b' values are indicators for classification in risk groups, their exact relative values have some bearing only within the same system and even this is only relevant for constant morphology, while complex morphologies are at flux.

Entropy is ruled out as a tool for network stability assessment because system entropy depends on iterations (Figure 10 and Figure 13 vs. Figure 12.2). Generalized entropy such as Tsallis entropy are ruled out owing to the dependence on CI for state probability estimator (state likelihood).

Ntropy is ruled out because as the number of iterations increases, Ntropy approaches 1; the outcome is a manifestation of the fact that entropy goes to maximum for all systems, rendering Ntropy/entropy useless for sorting different CPM systems. In cases such as in

Figure 13.1 where the system exhibits a small energy standard deviation (STDV) and selects the max-span-trees as attractors, Ntropy may start at 1 from the beginning. This attests to the fact that, in these scenarios, shorter span trees were not visited. Figures 13.2, 13.3, 13.4 prove that this outcome is misleading.
In Table 2 Ntropy .99 of cpm1 is smaller than that of CPM2 and Ntropy(CPM2)=Ntropy(CPM3)<Ntropy(CPM4)=Ntropy(CPM5) therefore Ntropy is ruled out.
Laplacian Variance trends inversely with entropy (Table 2).
Additionally, its quadratic amplification of the head of the power distribution introduces a bias, further compounded by the effect of the degree vector (d) in the denominator\
$(\sigma_{\mu}^2 = \frac{1}{d^2(N-1)} \sum_{i=2}^{N} |\mu_i - \bar{\mu}|^2)$.
Consequently, this measure is ruled out.
Eigenvalue variance is calculated from the weighted Laplacian ($\mathfrak{L} * H$).
Therefore, its values are dependent on iterations.
Eigen-ratio can be ruled out because CPM2 is no stabler than CPM1

PCA Analysis
In Figure 15 superposition of experiments 3,4,5 there is no correlation between vibration extrema in the eigen-vectors and CPM5 CP presented at the bottom. For instance, node 5 in an eigenvector maximum but it is in none of the CP, node 8 which is a minimum appears only once where 25 which is a minimum, is in all CP. Nodes 25 and 26 are equally important because they are coupled. Their different eigenvalues and vibration modes are not merited.
Eigen-spectrum is rejected.

Replicator function
Evolution is teleonomic [16], not statistic.
A part of the ($\mathfrak{L} \cdot A$) vector is incorporated on Figure 20.2. This section corresponds to the first 30 concurrent sequential activities.
There is no justification for the difference between $\mathfrak{L} \cdot A$ of the first 30 nodes, these nodes are all in one sequence, their effect on the CP is identical.
Consequently, this rules out all replicator-based stability predictive procedures such as Lyapunov stability.

Moreover, attempts to further generalize the trending of a dynamical system analysis are doomed to failure as the trending of CPM is unpredictable.

Simulations
As demonstrated above, CPM systems produce varying outcomes even under identical settings. To address this issue, simulations have been proposed in the literature [28]. However, simulations are susceptible to reification difficulties, and their results depend heavily on network morphology [29] and iterations. As shown here, initial morphology is arbitrary, dependent on expertise and chance, and morphological variations have complex effects. The above presentation rules out simulations as a prediction tool for CPM.

CPM

CPM mathematics assumes linear Markovian states and feed-forward loops. This assumption has been proved wrong in Case Study 2 and Case Study 4 respectively. Alternatively, the veracity of a Markovian assumption is based on Internal Variable Theory that suggests the effect of local variables that are not known to us, therefore cannot be incorporated in the model.

7. Discussion

CPM formulation was determined to be inadequate for modelling complex systems; CPM was found to be unstable and unpredictable; a salient example is that faults in CPM add, rather than ripple and inflate to avalanche [12]. All explicatory mathematical tools reviewed (Table 2) were found to be inapplicable as CPM stability evaluators, rendering CPM collapse unpredictable and unredeemable.

The five numerical experiments relate minimal difference networks for the same project; these are different sizes, different morphology networks for the same project. The discrete nature of **CPM networks** dictates the minimal morphological variations, such are the addition, deletion, or relocation of a node or an edge. **Viability kernels**, while small relative to the immensity of possible edges total number, are still large enough to allow for competing alternatives and provide significant room for expertise. Degree distributions are **power functions**, indicating that the network morphology is scale-free (Figure 7, Figure 8, Figure 9) and there are recurrent sub-formations (Figure 7.3). This is the consequence of WBS [21] and preferential attachment [30]. The networks centrality magnitude distributions are power functions with the power parameter $b<1$ (Figure 7, Figure 9), implying morphologies where the entire system forms one cluster [31]. As predicted by [12], "b" was negatively correlated with clustering (Figure 9) and centrality. "b" displayed a general correlation with the radius and a negative correlation with the small-world effect. Owing to the **morphology** of the networks, deterministic and self-adjusting alike, for all incoming spectrum of events, systems' response is complex, that is, local events have global effect, phenomena have the same morphology and traits on all scales (ergodicity); in our experiments the effects of the morphological variations were beyond prediction, that is, small or even minimal variations yielded the butterfly effect; this is an outcome of our sensitivity analyses; the ergodicity and universality traits of complexity ensure that these assertions are universal. LN(1.15,0.99), which is a **statistical** characteristic of construction projects, generated sufficient energy to unconditionally disrupt all CPM models, despite the use of a relatively low "b" power function relevant to well-managed projects. The stability under the regime of the lower variance LN(2,0.33), relevant to built infrastructure facilities, was also unpredictable.

It was shown that the longest paths are not necessarily the 'critical' ones suggested by CPM; they are unique morphological responses to chance and necessity. **CP** changes documented here are a spectator bias; it is we, the viewers, who submit the local (nodes) ad-hoc decisions to our model, thus portraying an outcome of local nodes perturbations into imaginary paths that travers the CPM conjured up networks.
This attribute of CPM is by itself ample justification to the falsification of all explicatory tools.

Simulations are widely suggested as a predictive tool that might overcome the CPM unpredictability, yet simulations were rejected here. Numerical experiments demonstrated that repetitive simulations yield different **CP** and **CI** even for a small number of repetitions (Figure 11.1Figure 11.2, Figure 12.2 vs. Figure 10). For the different networks of the same project, the results were entirely dissimilar. Experiment results of different scenarios for the same project were unpredictably varied. It is important to note that small variations in morphology are a daily occurrence in projects; moreover, different engineers generate different baselines for similar projects; added to it is faults stochastic effects that drive systems to binary choose different critical paths within the networks, causing yet again, different, possibly diametrically varied, CPM outcomes for the same projects and baselines.

The principle of maximum **entropy** [32] postulates that the probability distribution that best represents the state of knowledge of a system is the one with the largest entropy; the prospect of max entropy fairs no better in CPM, as CPM entropy changes with iterations. The suggestion of a new parameter Ntropy supplied proof to the contrary of entropy applicability; we demonstrated in our numerical experiments that with repetitions **Ntropy** goes to 1, i.e.., CI distribution tends to uniform, suggesting that in maximizing entropy the system tends to equal CI likelihood. Therefore, CPM as a projection tool is rejected.

The case studies reaffirm that CPM networks do not effectively represent complex systems (reification). A failed Critical Path does not necessarily predict a failed project, as seen in Case Study 3. The loss of stability indicates that the locus of the CP may change without necessarily compromising time or cost goals (Case Study 2). The E^4 Boolean cube analysis in Figure 22 demonstrates that all activities from a4 to a15 are coupled to the fourth degree, suggesting that every activity is revisited repeatedly, and the network iterates ad infinitum. Despite this, the project was successfully completed. Case Study 3 illustrates a **reification** fallacy: the network model does not accurately represent the project. The project did not experience a collapse, and being out of the attractor did not impact on its success. This fallacy is also evident in CPM3 to CPM5, which, although viable networks for the same project, fail to accurately represent the project. These models do not correctly represent the real nodes, edges, durations, constraints, and resources of the project. CPM Systems are susceptible to modeling **misrepresentation** also owing to of modelling errors (Figure 22), coupling (Figure 22), rework, imported risk (Figure 18), power plays (Figure 18), redesign (Figure 22), and networks' evolution (Figure 17, Figure 19); added to this are the complex modes of system response (Figure 12) to the statistics of perturbations (Figure 6). Moreover, nodes' content and links are predetermined in CPM, while actual activities change in content due to faults, design changes, and the effect of learning. Learning, central to productivity, is retained in systems morphology by continual readjustment. Morphology readjustment is not well-supported in CPM; the numerical experiments showed that morphological changes introduced to CPM networks may cause uncontrolled effects, the case studies add the destabilizing effect of **feed-back** on CPM. Workflow networks are **information networks**; feedback loops are a salient testimony to this (Case Study 4). A physical link between activities entails an information link, but the opposite is not valid; these implies cybernetics. CPM networks represent activity networks rather than information networks; information links are an origin of misrepresentation in CPM; moreover, information edges are bidirectional, while CPM networks are not well-equipped to deal with loops; fault multiplication, propagation, and avalanche are enabled via information links, while CPM representation of these is limited.

Changing CPM3 to CPM4 and CPM5 enhanced teleonomic coherence, Small-World effects, and **synchronization** (Figure 16); entropy was reduced (Figure 12). CPM5 was stabler in our simulations, although it has the longest and most numerous CPs. Is this outcome a general tendency? Can it be suggested that well-planned projects are more stable in CPM? Figure 13 attests to the contrary: CPM model stability goes down while actual project stability goes up. Synchronous production is promoted in project management because it generates metastable **minimum entropy dissipative structures** [33]. An industrial line of mass production is a fixed production line with synchronized concurrent activities; activities are designed to be constant flow time-invariant dissipative structures of minimum entropy production [34], where the autonomy of agents is minimized. The detrimental effects of unsynchronized activities are mathematically portrayed in [12]. Yet in CPM, synchronization causes correlated avalanches. This is another discrepancy between CPM models and reality (portrayed in Case Study 2 and Case Study 3). In case study 3 we demonstrated that in a sequence of concurrent production line, the CPM model acquires the latencies of the nodes, creating an attractor, while in real synchronous production lines, latencies are not allowed to accumulate. One would expect that replacing a sequence of activities with a hammock would have altered that result, reducing complexity and variance, while retaining teleonomic content; Case Study 4 is an example to the contrary. Simplifying networks by replacing loops, feedback mechanisms, and recurrent modular formations with hammocks introduces a variety of new issues, such as information loss, edges coherence forfeiture, ripple effects within hammocks, and between hammocks.

Off-site production, such as portrayed in Case Study 4 precast facility, is of lower entropy; this causes higher entropy in the receiving system. This phenomenon is established on Case Studies 1 and 2 Figure 19, and the opposite effect of concurrent in-situ production of Case Study 3. The explanation is that total entropy increases due to the addition of states, which leads to the redistribution of this added **entropy** across the system's sites. This phenomenon arises from various factors:

Morphology	The system's degree is higher, involving additional networks and subsets of internal hierarchies.
Time Management	Contradictory schedules of subcontractors with general contractor scheduling cause stoppages (stuttering) and collisions [12].
Production	Mismatches in production standards, such as tolerance, add to the system's complexity.
Opposing Interests	Independent agents with diverse interests create additional entropy [34].
Design	Design becomes integrated into the production process, introducing rework loops and further complicating the system [35].

These factors contribute to the growing entropy and its redistribution within the network [12], (Figure 22).

Decision rules used in the numerical experiments affect the velocity of system evolution. The rules chosen here are an underestimation of reality, yet the results are definitive.

Low quality projects are stabler in CPM; this statement is supported in the numerical experiments where t>1 enables bigger open faults, and without the dissipative effect of small faults, their impact is stronger, thus the system devolves faster. This is the curse of good projects to suffer from higher magnitude faults [12].

The suggestion by ToF that relevant statistics are open fault statistics is validated here by the numerical experiment. Additionally, the idea that the relevant morphology is the **information system**'s morphology is supported by Figure 22; Figure 22 clearly shows that the network in question is an information network, where information flows through the coupled (rework) edges.

Infrastructure facilities exhibit a **topological similarity** to the network representation of projects [36]. However, the network's constituents differ in meaning and outcome. Edges may represent conduits and node junctions such as manholes and pumping stations, where edge weights may represent capacity or flow. The longest path duration in a drainage system determines the time for full capacity. Coupled activities are a loop, they may produce effects such as backwash and coupled tanks.

Using the LN(2,0.33) adjusted drainage system PDF, it has been demonstrated in the numerical experiments that a network may produce a relatively stable CP/CI on the longest paths (Figure 14.1). Some iterations even resulted in Ntropy=0, which is a stable attractor. In infrastructure facilities, there are attractors corresponding to that experiment. The attractors are used in ToF for prediction of trajectories, emergent behaviors, and entropy trending for avalanche prediction and correction [35].

For project managers seeking a time management framework, we suggest that **minimum teleonomic information networks** be produced on Gantt forms, with constraints and supply chain explicitly presented, deliberately setting the core production sequences as CP (as portrayed in experiment CPM5). This network should be fed to CPM to weed out competing long paths.

***Further study*:** minimum teleonomic information networks, their generation, topological and information content equivalence and entropy implications are left for further tur study.

The **hypothesis** that CPM networks' evolution and stability are determined by statistics and morphology was thoroughly justified throughout the article. The role of statistics was challenged in further research, suggesting that complexity is not stochastic and that predictability may arise from chaos.

8. Summary and Conclusions

CPM is rejected as a tool to manage complex projects.

CPM networks are inherently unstable due to their scale-free morphology, which leads to a complex system response. Moreover, even minimal modifications in morphology can cause unpredictable outcomes. The experiments showed that when exposed to risks relevant to construction projects, all networks lose stability. This instability was evident through variations in the Critical Path and Criticality Index.

CPM models failed to accurately represent actual projects due to various modeling limitations. Added to these are constant morphological evolution, coupling, redesign, constraints, and the complex, rather than CPM linear, effects. Additional factors such as imported risk, exogenic disruptors like power plays (Figure 18), and endogenic factors like the quality of management also contributed to the reification of CPM. Viability kernels are diverse enough to allow for different CPM networks to be developed for the same project, resulting in different outcomes and making expertise a key factor in stability.

It was demonstrated that networks are information networks, unlike CPM production flows. Information networks have feedback loops, rework processes, modular recursive formations, sub-networks, bridges, and they are molded by learning. These attributes are not well-modelled by CPM.

Stalwart tools for stability assessment were rejected. Morphological tools like entropy were found to be iteration-dependent, while PCA proved inadequate in the face of exogenic influences. The replicator function failed to account for the stochastic nature of change, statistical tools such as variance were confounded by complexity, and simulations were hindered by modeling limitations.

Project **M**anagement **praxis** suggests coherence, synchronization, and small world effects, dictating concurrent synchronous production sequences as Critical Paths. These lessons, that promote entropy minimization within dissipative structures, generate contrary effects in CPM networks.

It was also shown that dimensionality reduction by minimum teleonomic networks (here hammocks) was not helpful in reducing entropy. Further research is required to deliberate whether alternatives for dimensionality reduction are applicable.

The contribution of this manuscript is in the dismissal of CPM use as a managerial tool for complex systems, and in providing explanations to CPM inadequacy. CPM use is advocated as a complementary tool for network design, to be used to weed out alternative long paths.

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Data Availability: The data presented in this study is openly available in a publicly accessible repository. The database of which case studies 1-3 were taken from is publicly available on the supporting website www.or-as.be/research/database (OR-AS, 2014a). Case Study 4 is in DOI: 10.1061/(ASCE)CO.1943-7862.0002277. The data generated here is presented in the Experiment section.

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