The Role of Correlations Between Activity Durations in Project Schedule Risk Analysis

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1. Introduction

The literature on project management highlights correlations between activity durations in real projects and their influence on project performance. In many cases, the correlations are due to the presence of common risk factors affecting multiple activities simultaneously: adverse weather conditions (Acebes et al., 2014), resource availability or labour productivity (and expertise), design errors and changes in the scope of the project that affect several activities, etc.

Negative correlations also occur. For example, due to the learning effect, i.e., the experience and knowledge gained in one activity can make teams more efficient in other activities requiring similar skills (Edmondson & Nembhard, 2009). Negative correlations may also arise from managerial or resource-driven compensatory decisions, e.g., reactive scheduling (Herroelen & Leus, 2005). Delays in one activity trigger acceleration, resource reallocation, or scope adjustments in another activity, leading to an inverse relationship between their durations. Also, negative correlations are result of decisions to overlap activities or the implementation of fast-tracking, where delays in upstream activities force downstream tasks to reduce their duration through reduced rework or increased parallelization (Krishnan et al., 1997).

CPM and PERT literature usually consider that activity durations are independent (MacCrimmon & Ryavec, 1964; Vanhoucke, 2013). Banerjee & Paul (2008) alert that correlation between activity durations can affect PERT bias.

The assumption of independence was also inherited by much of the Schedule Risk Analysis (SRA) practice. Although simulation would explicitly allow correlation to be introduced, in most industrial and academic applications, the simplified assumption of independence has been retained (Ökmen & Öztaş, 2008; Yang, 2007)

However, correlations between activity durations can affect project uncertainty and its statistical characteristics (Kaut et al., 2021). Van Dorp & Duffey (1999) show that correlations affect the distribution shape of the project total duration, and the changes are higher the higher the size of the project (number of activities). Similar studies have concluded that activity correlation can affect the expected duration of a project and its variance.

In this paper, we go one step further and investigate how correlations can influence risk sensitivity indexes, such as criticality (CI, the probability of the activity to fall on the critical path, cruciality (CrI, the correlation between the duration of an activity and the total project duration) and SSI (critically multiplied by the quotient between the standard deviations of the activity and the project). To this aim, we perform Monte Carlo simulations, comparing results with and without correlations.

After verifying that correlations do indeed change some of the sensitivity indexes, we wonder to what extent different variables in the network topology affect these changes. Specifically, we asked ourselves how the series-parallel (S/P) degree, or the presence of critical paths with similar or different durations, affects these changes. We also studied the influence of the network's degree of tightness, using a new indicator, Project Tightness (PT) (Acebes & Pajares, 2025). PT quantifies the degree of compression or “tension” in the schedule, taking into account both slack in activities and the configuration of the project's critical structure, and normalizes the total slack by the number of activities not on the dominant critical path.

Our results show that correlations have a significant impact on project variance, cruciality, and SSI; S/P is relevant, but PT has a greater impact on correlations' effects on sensitivity indexes.

This research has practical implications for project risk management and monitoring. The objective of the SRA methodology (Hulett, 1996) is to identify which activities contribute most to the project's total variability. To do this, the sensitivity indexes of the different activities are estimated, and threshold values are set, so that monitoring and control efforts are intensified in those activities that exceed them (Vanhoucke, 2010). Consequently, if correlations change the values of the sensitivity indexes, the activities on which to focus monitoring efforts will differ from those considered when there are no correlations.

2. Simulations and results

A controlled Monte Carlo simulation experiment was conducted on artificially generated project networks to analyse the impact of activity-duration correlations under different topological conditions. Artificial networks were generated using RANGEN, systematically varying their series–parallel degree (SP) and Project Tightness (PT) in order to obtain structurally diverse project configurations. For each SP–PT configuration, a large number of Monte Carlo simulation runs were performed.

Activity durations were modelled as stochastic variables and analysed under four correlation scenarios: positive and negative correlation (±0.8) between two activities located either on the same path or on different paths. These scenarios were compared against a baseline case assuming independent activity durations. Correlation was introduced pairwise to isolate its effect and ensure comparability across scenarios. For each experimental setting, relative changes with respect to the baseline case were computed for project mean duration, variance, and the 90th percentile (P90) of the makespan distribution. In addition, activity risk-sensitivity indexes commonly used in Schedule Risk Analysis—criticality (CI), cruciality (CrI), and the Schedule Sensitivity Index (SSI)—were estimated and analysed comparatively across topological configurations.

In this section, we show the results of the simulations performed using the software MCSimulRisk (Acebes et al., 2023). Artificial project networks with different topologies were generated using RANGEN (Demeulemeester et al., 2003).

In Table 1, the first and second columns refer to the project network topology (SP series/parallel, PT Project Tightness). The following columns show, in percentage, the increments (decrements) in the project mean, variance, and the 90% percentile of the total project duration distribution, when there are correlations in the project (between two activities), compared to the scenario with no correlation. We show scenarios in which correlated activities are on the same (S) or different (P) path. The numbers in brackets are the correlation values (i.e., +0.8 or -0.8).

We see that, regardless of the network topology, the increase in the project mean duration is not very different when correlations are introduced (changes below 1%). However, correlations produce a significant increase (a decrease when negative), especially when they affect activities along the same path (S). For instance, with a correlation of +0.8, SP=0.111, and low PT, the maximum increment in variance is 78.64%; correlations produce a significant change in project uncertainty. However, if activities are on different paths, the increment is only 1.139%.

Furthermore, the variance increment appears to increase with SP, and for the same value of SP, projects with low tightness (PT Low) exhibit a much higher variance increment than those with high tightness.

Table 1. Influence of correlations and net topology on mean, variance, and 90 th percentile

Topological Index		ΔMean (%)				ΔVar (%)				ΔP90 (%)			
SP	PT	S(+0.8)	S(−0.8)	P(+0.8)	P(−0.8)	S(+0.8)	S(−0.8)	P(+0.8)	P(−0.8)	S(+0.8)	S(−0.8)	P(+0.8)	P(−0.8)
0.111	Low	0.149	-0.015	0.113	-0.030	78.460	-77.485	1.139	-0.299	3.620	-4.937	0.186	-0.047
0.111	High	0.331	-0.312	-0.185	0.080	12.701	-4.708	5.334	-9.415	0.712	-0.221	0.101	-0.167
0.333	Low	0.085	-0.042	0.054	-0.070	42.322	-40.281	0.085	-1.013	1.548	-1.544	0.172	-0.121
0.333	High	0.232	-0.228	-0.037	-0.062	51.027	-48.595	10.906	-11.737	1.774	-1.990	0.015	-0.108
0.556	Low	0.075	0.004	0.053	-0.042	48.698	-48.800	1.263	-2.298	1.717	-1.793	0.123	-0.115
0.556	High	0.151	-0.091	-0.205	0.198	13.908	-7.492	8.246	-13.434	0.504	-0.172	0.035	-0.055
0.778	Low	0.016	-0.036	0.034	-0.058	31.847	-27.282	1.074	-0.820	0.840	-0.815	0.153	-0.027
0.778	High	0.205	-0.117	-0.250	0.111	7.178	-8.031	10.803	-14.831	0.377	-0.260	-0.134	0.015
0.889	Low	0.010	0.008	0.026	-0.012	40.071	-42.553	-2.057	-0.591	1.108	-1.221	-0.036	-0.002
0.889	High	0.146	-0.033	0.027	0.027	31.994	-32.540	14.090	-11.774	0.816	-0.846	0.135	-0.020

Table 2 summarises the same experimental scenarios and shows the variations in criticality (CI), cruciality (CrI), and SSI. Changes in CI remain small across all cases, with maximum deviations below six points, confirming that correlations have a limited effect on the probability of activities becoming critical.

Table 2. Influence of correlations and net topology on criticality, cruciality and SSI.

Topological Index		ΔCI				ΔCrI				ΔSSI			
SP	PT	S(+0.8)	S(–0.8)	P(+0.8)	P(–0.8)	S(+0.8)	S(–0.8)	P(+0.8)	P(–0.8)	S(+0.8)	S(–0.8)	P(+0.8)	P(–0.8)
0.111	Low	-1.012	-0.656	0.252	0.536	57.233	-60.412	59.723	58.287	-19.614	84.831	0.595	-0.490
0.111	High	4.744	-5.784	-4.308	3.136	33.294	-15.641	21.952	-14.061	4.301	-5.327	-4.774	5.003
0.333	Low	0.340	-0.076	-0.396	0.428	42.237	-39.811	57.098	55.724	-11.640	22.399	0.808	-0.808
0.333	High	-2.924	-3.764	-3.332	2.468	30.376	-13.854	38.336	26.421	-5.356	6.372	-5.640	3.976
0.556	Low	0.004	0.000	0.000	0.000	43.901	-36.830	43.447	43.411	-14.119	31.510	0.802	1.082
0.556	High	3.512	-4.140	-5.268	-3.940	33.183	-13.460	43.960	-24.811	-2.542	2.804	-6.257	7.254
0.778	Low	0.000	0.000	0.000	0.000	40.070	40.897	44.343	43.979	-7.172	9.915	0.807	-0.642
0.778	High	1.180	0.688	5.548	-4.688	15.315	-18.119	49.108	17.081	-2.507	1.949	-5.063	6.842
0.889	Low	0.000	0.000	0.000	0.000	28.166	-40.413	41.668	41.686	-8.312	17.165	0.642	0.562
0.889	High	-0.752	0.504	-1.644	-1.460	25.806	-34.314	52.995	25.295	-5.874	9.785	-6.359	6.969

By contrast, CrI exhibits substantial variations in every scenario. The most pronounced positive and negative shifts appear consistently in networks with low PT, where ΔCrI values frequently exceed ±55 points. SP acts as a secondary amplifying factor: within low-PT configurations, the largest shifts occur when SP is also low. However, the comparison across scenarios shows that PT is the dominant factor moderating the sensitivity of CrI to correlations, as high-PT networks exhibit much smaller changes even under identical SP conditions and correlation patterns.

SSI follows a different behaviour. Its largest increments arise under negative correlations and when the correlated activities belong to the same path, with values exceeding +80 points in some low-SP/low-PT cases. This reflects a stronger transmission and amplification of variability along the dominant project chain when negative dependence affects sequential activities.

Figure 1 provides a graphical summary of the ΔCrI distributions across the SP–PT scenarios. The boxplots highlight the much wider dispersion and larger shifts associated with low-PT networks, and show how these effects are further intensified when SP is also low, confirming the patterns observed in Table 2 for both positive and negative correlations.

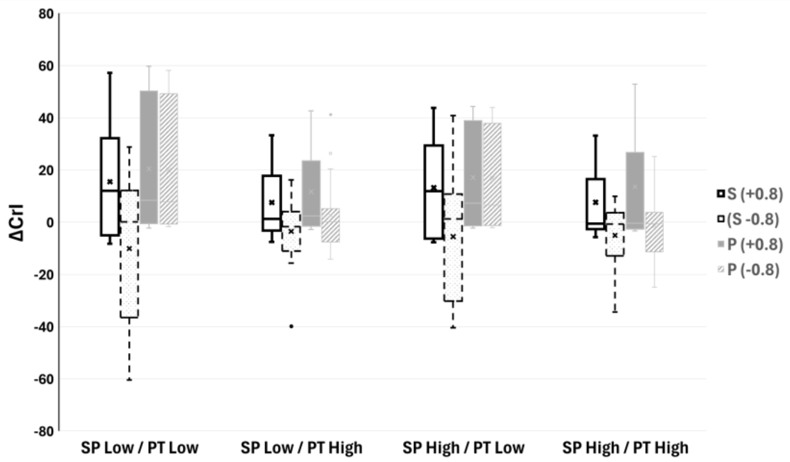

Figure 1. Distribution of ΔCrI across the four SP–PT scenarios, comparing positive (+0.8) and negative (–0.8) correlation.

3. Conclusions

In this paper, we have studied how correlations in project activity durations affect project uncertainty and activity risk-sensitivity indexes. In line with previous literature, we confirm that positive/negative correlations increase/decrease total project variance, with larger effects observed in projects with low SP and PT.

We take one step further by investigating how correlations and project network topology influence the values of risk-sensitive indexes, especially CrI. Both SP and PT help explain the observed differences in their variations, with low SP and PT values implying greater variability of the indexes.

According to our results, project managers should reflect during the project planning phase on potential sources of correlation between activity durations and consider, at least qualitatively, how their presence may affect risk control and monitoring practices during the execution phase.

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