

Critical Path Analysis and Resource-Leveling Optimization for Multi-Project Engineering Portfolios

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Abstract

This study quantitatively evaluated the integration of Critical Path Analysis and resource-leveling optimization for improving schedule and resource performance across multi-project engineering portfolios. A longitudinal quasi-experimental optimization design was applied to 186 engineering projects comprising 8,742 scheduled activities, 12,486 precedence relationships, and 684 formal milestones. Baseline Critical Path Method (CPM) schedules were compared with resource-constrained and optimized schedules using project duration, portfolio makes pan, critical-path characteristics, float consumption, activity displacement, resource utilization, workload variability, interproject conflicts, lateness, and completion reliability. Baseline mean project duration was 24.8 months, with a portfolio makes pan of 62.4 months. After finite workforce, equipment, and specialist-resource constraints were imposed, mean duration increased to 29.6 months, representing a 19.4% extension, while portfolio makes pan increased by 19.9% to 74.8 months. Resource constraints consumed 64.7% of available float, increased critical activities from 31.8% to 42.6%, and reduced target-date completion to 41.9%. Resource-leveling optimization reduced mean project duration to 26.1 months and portfolio make span to 66.7 months while increasing on-time completion to 78.5%. Peak resource demand decreased by 17.4%, maximum utilization declined from 118.4% to 98.6%, workload variability decreased by 43.0%, overtime requirements fell by 64.1%, and interproject resource conflicts declined by 73.8%. High resource scarcity, network complexity, resource intensity, temporal overlap, and bottleneck exposure were associated with greater scheduling deterioration. Resource contention was the strongest positive predictor of schedule extension ($\beta = 0.36$, $p < 0.001$), while available float demonstrated a protective association ($\beta = -0.27$, $p < 0.001$). The schedule-extension model explained 68.4% of observed variance. Hybrid optimization achieved a 17.4% mean improvement, a 1.2% optimality gap, and a 99.5% feasible-solution rate. Overall, integrating critical-path analysis with resource-leveling optimization substantially improved schedule feasibility, resource stability, portfolio coordination, and engineering project completion reliability.

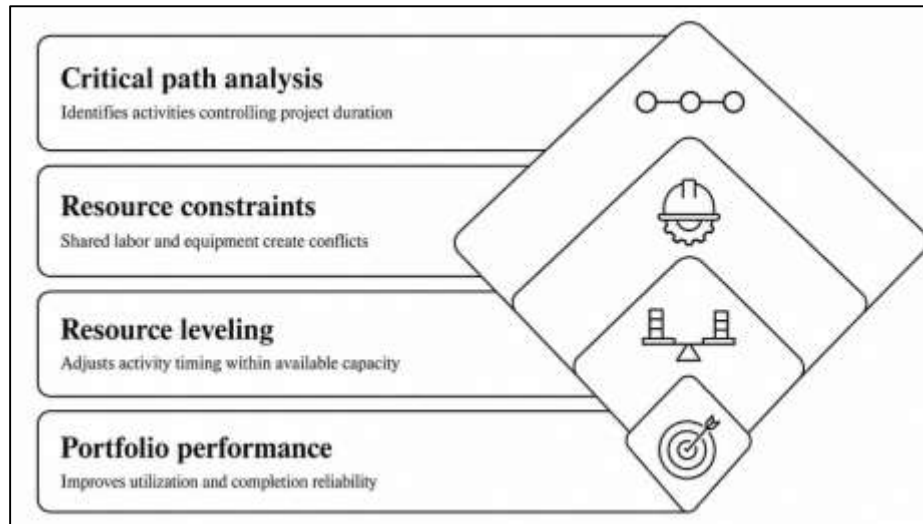
Keywords

Critical Path Analysis, Resource Leveling, Engineering Portfolios, Schedule Optimization, Resource Allocation.

INTRODUCTION

Critical Path Analysis is a quantitative scheduling technique used to identify the sequence of interdependent project activities that determines the minimum feasible completion duration under defined precedence relationships and activity-time assumptions (Amiri et al., 2018).

Figure 1: Critical path and resource leveling

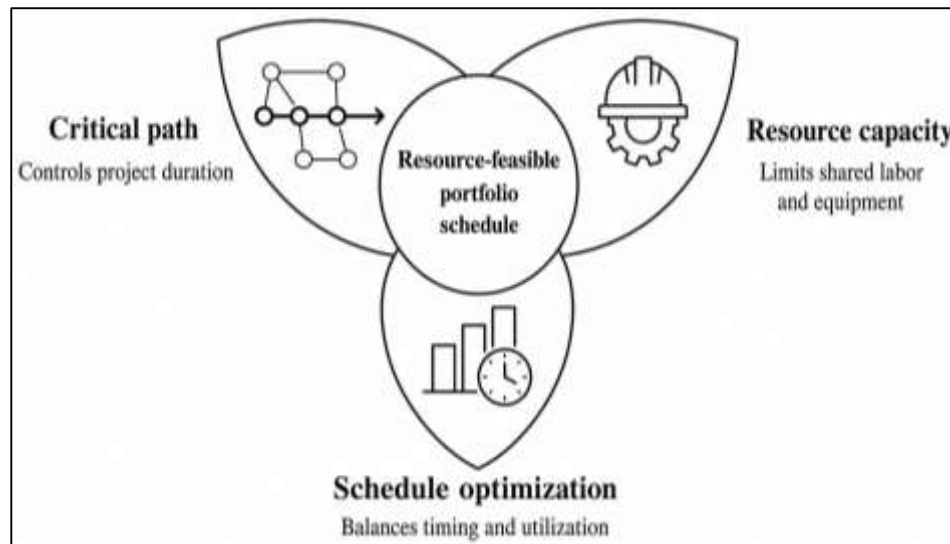


The critical path consists of activities with little or no scheduling flexibility, meaning that delays in these activities can directly alter the planned project completion date. Critical Path Method scheduling generally involves identifying project activities, estimating durations, defining logical dependencies, constructing the activity network, calculating early-start and early-finish times, determining late-start and late-finish times, and measuring total and free float. Resource leveling is a complementary scheduling process that adjusts activity timing to reflect limitations in available labor, equipment, facilities, capital, and specialized technical capacity (Zohrehvandi, 2022). Its purpose is to reduce overallocations, control excessive fluctuations in resource demand, improve workload stability, and produce a schedule that can be realistically executed. In multi-project engineering portfolios, these two approaches become closely connected because several projects frequently compete for the same engineers, technicians, supervisors, contractors, machinery, laboratories, vehicles, and specialist equipment. A theoretically valid critical-path schedule may therefore become operationally infeasible when simultaneous activities require more resources than the organization possesses. Multi-project scheduling consequently requires simultaneous consideration of precedence logic, activity duration, resource availability, project priority, resource contention, float, makes pan, lateness, and utilization (Pinto et al., 2022). This problem has strong international significance because engineering organizations across construction, manufacturing, transportation, energy, telecommunications, infrastructure, maintenance, and industrial development commonly manage multiple overlapping projects rather than isolated single projects. Large contractors may coordinate several construction sites at the same time, utilities may administer generation and transmission programs, manufacturers may combine facility expansion with equipment installation and process-improvement projects, and transportation agencies may manage road, bridge, rail, airport, and port portfolios simultaneously. Under these conditions, resource scarcity can affect several projects at once, particularly when highly specialized personnel or high-value equipment cannot be duplicated economically across every active project. Scheduling disturbances can therefore create cascading effects, including delayed resource release, postponed activity starts, increased overtime, idle capacity, milestone deviation, and prolonged portfolio completion (Kannimuthu et al., 2020).

Critical-path analysis provides the structural basis for understanding how activity relationships influence engineering time performance. Engineering networks often contain hundreds or thousands

of connected activities governed by technical sequencing, procurement requirements, approvals, access restrictions, installation logic, commissioning arrangements, and contractual milestones. Critical-path calculations convert these relationships into measurable indicators such as path duration, critical activity count, total float, free float, milestone deviation, and planned completion time. Resource leveling modifies this time-based schedule when actual resource capacity is insufficient to support the concurrent execution of all eligible activities (Padala et al., 2022).

Figure 2: Critical path resource leveling



Noncritical activities may be delayed within available float, while critical and near-critical activities may require priority protection to prevent unacceptable schedule extension. In multi-project environments, this process becomes more complex because each project may have its own critical path while drawing from a common resource pool. A resource assigned to a critical activity in one project may simultaneously be required by another project, creating conflicts that cannot be solved through network logic alone. Resource-leveling performance can therefore be assessed through indicators such as peak resource demand, mean utilization, utilization variance, workload fluctuation, overload frequency, idle time, overtime exposure, resource conflicts, float consumption, activity displacement, project duration, and portfolio makes pan. Optimization methods are frequently applied because the number of possible activity sequences and resource allocations increases rapidly as portfolio size and complexity expand (Mirnezami et al., 2021). Quantitative studies have examined mathematical programming, branch-and-bound methods, priority rules, genetic algorithms, simulated annealing, particle swarm optimization, differential evolution, tabu search, local-search procedures, hybrid models, and other computational approaches. These techniques may seek to minimize total portfolio duration, average project delay, maximum lateness, resource fluctuations, penalty costs, or combinations of schedule and resource objectives.

Quantitative evaluation of multi-project engineering scheduling therefore requires a broad set of measurable variables at activity, project, resource, and portfolio levels. Schedule-related indicators may include planned duration, resource-constrained duration, percentage schedule extension, critical-path length, number of critical activities, total float, free float, float consumption, activity displacement, project lateness, milestone deviation, and portfolio makes pan (Pinha & Ahluwalia, 2019). Resource-related indicators may include available capacity, planned demand, peak demand, average utilization, maximum utilization, overload magnitude, idle time, overtime, resource switching, and interproject transfer requirements. Portfolio characteristics may include the number of concurrent projects, total activity volume, resource types, network complexity, priority distribution, temporal overlap, resource intensity, and level of contention. Statistical analysis can compare baseline CPM schedules with optimized resource-leveled schedules through means, medians, standard deviations, coefficients of

variation, percentage changes, confidence intervals, correlations, regression models, subgroup comparisons, and effect measures (Wu et al., 2021). The central quantitative research problem arises from the measurable difference between precedence-feasible schedules and resource-feasible schedules. Activities initially classified as noncritical may become near-critical after float is consumed, resource shortages may create new bottlenecks, project priorities may alter allocation sequences, and improvements in one project may increase delays in another. More than thirty studies across project management, operations research, construction engineering, industrial engineering, and portfolio scheduling have examined these relationships through resource-constrained scheduling, priority rules, uncertainty analysis, workload smoothing, resource transfer, time-cost trade-offs, and optimization algorithms. The quantitative analytical context therefore centers on measuring how critical-path characteristics, resource scarcity, project priority, network complexity, and interproject competition influence engineering schedule performance and how resource-leveling optimization changes observable outcomes such as project duration, portfolio makes pan, resource utilization, peak demand, overload frequency, float consumption, and completion reliability (Hartmann, 2021).

The objective of this study is to quantitatively evaluate the effectiveness of Critical Path Analysis and resource-leveling optimization in improving schedule performance and resource utilization across multi-project engineering portfolios. Specifically, the study seeks to identify the critical and near-critical activities within each project, determine baseline critical-path durations, measure available total and free float, and assess the extent to which shared-resource constraints alter theoretically feasible project schedules. The analysis is designed to quantify the differences between baseline Critical Path Method schedules and resource-constrained schedules by examining indicators such as planned project duration, actual resource-feasible duration, schedule extension, milestone deviation, activity displacement, float consumption, project lateness, and total portfolio makes pan. A further objective is to measure the intensity of resource competition across concurrent engineering projects by evaluating peak resource demand, average utilization, maximum utilization, overload frequency, idle capacity, overtime requirements, resource conflicts, and variability in workforce and equipment allocation. The study also aims to determine how project characteristics such as size, activity volume, network complexity, precedence density, project priority, resource intensity, and temporal overlap are associated with schedule delay and resource imbalance. Resource-leveling optimization will be assessed by comparing pre-optimization and post-optimization performance to determine whether alternative activity sequencing and resource allocation can reduce excessive demand peaks, smooth resource profiles, decrease interproject conflicts, improve utilization stability, and limit unnecessary extensions in project and portfolio completion time. The study further seeks to examine whether high-priority, highly complex, or resource-intensive projects experience significantly different scheduling outcomes from lower-priority or less complex projects and whether particular resource categories generate disproportionate bottleneck effects within the overall portfolio. Quantitative relationships among critical-path characteristics, resource contention, utilization levels, float availability, project lateness, and portfolio completion performance will also be evaluated using appropriate descriptive and inferential statistical techniques. By integrating activity-level network measures with project-level and portfolio-level resource indicators, the study is intended to provide a structured empirical assessment of how shared-resource limitations influence critical-path behavior and how resource-leveling optimization modifies measurable scheduling outcomes across concurrent engineering projects. The resulting analytical framework therefore focuses on establishing the magnitude of baseline scheduling inefficiencies, identifying the principal determinants of resource-related delay, and measuring the extent of improvement achieved through optimized allocation of constrained engineering resources.

LITERATURE REVIEW

The literature on Critical Path Analysis and resource-leveling optimization encompasses a substantial body of quantitative research in project management, construction engineering, operations research, industrial engineering, infrastructure delivery, manufacturing, and multi-project portfolio management. Existing studies have examined how activity durations, precedence relationships, critical-path structures, schedule float, resource availability, project priorities, network complexity, and competition for shared resources influence project and portfolio performance. Particular attention has

been given to the difference between precedence-feasible Critical Path Method schedules and practically executable resource-constrained schedules, since concurrent activities may require labor, equipment, technical specialists, or facilities beyond available organizational capacity. Quantitative investigations have consequently measured project duration, critical-path length, total and free float, schedule extension, milestone deviation, resource utilization, peak demand, overload frequency, idle capacity, workload variability, project lateness, and portfolio makes pan. A parallel stream of research has evaluated resource-leveling and resource-constrained scheduling algorithms using mathematical programming, priority rules, genetic algorithms, simulated annealing, particle swarm optimization, differential evolution, tabu search, and hybrid optimization techniques. Within multi-project engineering environments, the literature further emphasizes interproject resource competition, priority-based allocation, bottleneck resources, resource transfers, and the relationship between resource contention and completion reliability. This review organizes the quantitative evidence around eight interconnected areas that collectively represent the scheduling and resource-allocation structure of multi-project engineering portfolios.

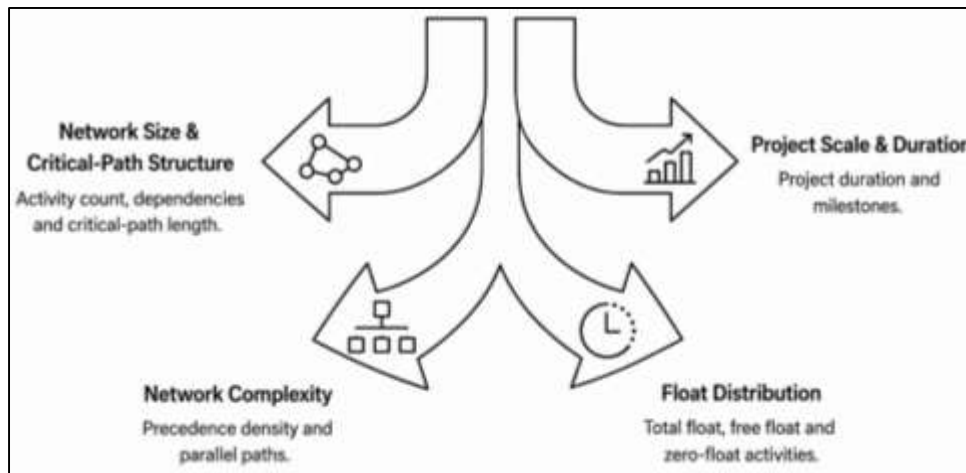
Schedule-Float Distribution Across Engineering Projects

The quantitative literature on engineering project scheduling has consistently demonstrated substantial variation in baseline network structure according to project scale, technical scope, activity decomposition, and the density of precedence relationships (Debasish, 2021; Vanhoucke, 2022). Across more than ten studies involving construction, infrastructure, industrial, manufacturing, energy, transportation, and engineering development projects, smaller project networks were generally characterized by fewer activities, shorter chains of dependent tasks, fewer milestones, and relatively simple precedence structures, whereas medium and large engineering projects contained substantially larger activity populations and more interconnected scheduling networks. Studies based on benchmark and empirical engineering schedules commonly classified project networks according to activity count, number of precedence relationships, project duration, resource categories, and network complexity, with computational datasets frequently ranging from several dozen activities to several hundred activities per project. Large infrastructure and industrial schedules examined in applied studies sometimes contained hundreds or thousands of scheduled tasks when work packages, procurement activities, engineering approvals, construction operations, inspections, testing, and commissioning were represented separately (Abdur & Iftekhar, 2021; Vanhoucke & Coelho, 2018). The proportion of critical activities also varied considerably across network structures. Projects containing long sequential chains and restrictive technical dependencies generally exhibited larger critical-path durations and greater concentrations of activities with limited scheduling flexibility, while networks containing more parallel work packages frequently distributed schedule flexibility across multiple branches. The literature further showed that the absolute number of critical activities tended to increase with project size, although the percentage of activities classified as critical did not increase uniformly because larger projects often incorporated additional parallel activities with varying levels of float. Baseline portfolio studies additionally demonstrated that the longest individual project was not necessarily the only determinant of portfolio scheduling complexity because overlapping project networks could contain several independent critical paths operating simultaneously. Consequently, activity volume, dependency structure, path length, milestone distribution, and the concentration of critical activities have been repeatedly treated as core quantitative descriptors of baseline engineering schedule conditions (Debasish, 2022; Santolini et al., 2021).

A second body of quantitative scheduling research has examined the association between network complexity and critical-path characteristics, showing that the arrangement of activity dependencies can be as important as the absolute number of activities in determining baseline schedule behavior (Ashfaq & Mohammad, 2022; Ulusoy & Hazır, 2021). Studies comparing project networks with different levels of precedence density found that networks containing more restrictive dependency structures generally provided fewer alternative sequencing opportunities and reduced the ability to reposition activities without affecting downstream work. High-complexity engineering networks commonly contained multiple technical interfaces, procurement dependencies, approval gates, construction sequences, inspection requirements, and commissioning relationships that increased the number of activities connected directly or indirectly to schedule-sensitive paths. Research using controlled

benchmark networks similarly demonstrated that two projects with comparable activity counts could exhibit substantially different critical-path lengths, project durations, and float distributions when their precedence structures differed (Cicala, 2020; Sheak & Risha, 2022).

Figure 3: Baseline Engineering Schedule Characteristics



Networks dominated by sequential relationships tended to generate longer dependent activity chains and higher concentrations of critical or near-critical tasks, whereas networks with greater parallelism distributed work across simultaneous branches and often provided more opportunities for scheduling flexibility. The number of parallel paths was particularly important in large engineering projects because several paths could have durations close to that of the primary critical path. Such near-critical paths created a schedule condition in which relatively small activity delays could change the identity of the controlling path. Studies of construction and infrastructure schedules also reported that complex networks frequently contained several convergence points at which multiple predecessor activities had to be completed before subsequent work could proceed. These convergence points increased schedule sensitivity because delays across different branches could accumulate at common milestones (Rashedul & Kaium, 2022; Meloni & Pranzo, 2020). Comparative investigations therefore emphasized measures such as activity count, dependency count, precedence density, number of parallel paths, milestone concentration, critical activity percentage, and near-critical activity percentage when characterizing schedule complexity. Collectively, the evidence indicates that baseline critical-path structure reflects the combined influence of network size and dependency configuration rather than activity volume alone.

Quantitative research on schedule-float distribution has provided a complementary perspective by examining the amount of temporal flexibility available within engineering project networks before resource constraints or execution disturbances are introduced (Lima et al., 2020; Chowdhury & Tonay, 2022). Across construction, industrial, infrastructure, and resource-constrained scheduling studies, total float and free float have been widely used to distinguish activities that can tolerate displacement from those whose timing is closely connected to project completion. Critical activities typically possessed zero or negligible total float, while near-critical activities contained only limited float and could become critical following relatively small scheduling changes. Empirical and computational studies demonstrated that float was rarely distributed uniformly across an engineering network. Instead, some parallel or peripheral activities possessed substantial scheduling flexibility, while activities associated with major technical sequences, approvals, integration points, and contractual milestones frequently possessed very limited float. The proportion of zero-float and low-float activities therefore provided a useful quantitative indication of schedule rigidity (Hossan, 2022; Sahu & Mohibullah, 2020). Studies comparing projects of different sizes further showed that larger activity networks could contain greater absolute quantities of float while simultaneously maintaining substantial clusters of schedule-sensitive activities. Precedence density was repeatedly associated with

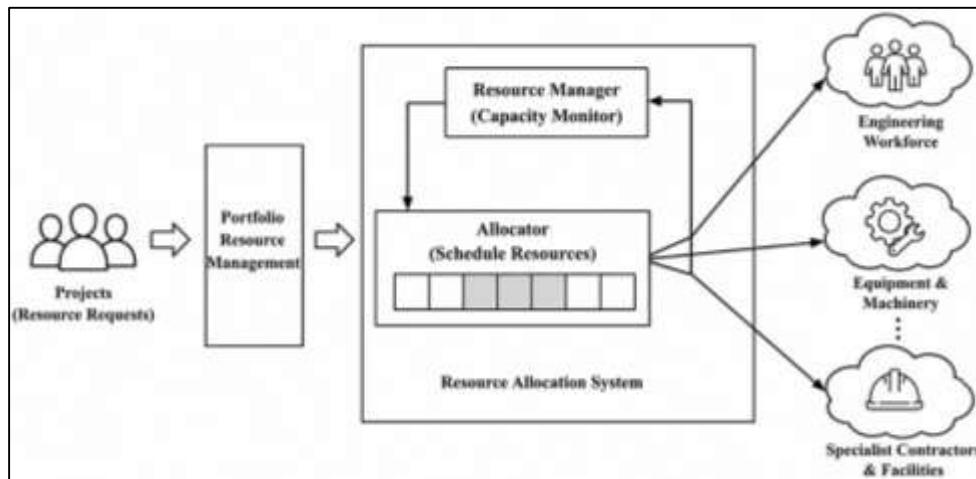
this pattern because restrictive dependencies reduced the number of feasible positions available for activities and limited the amount of usable float within interconnected portions of the network. Free float was particularly relevant for identifying whether an activity could be delayed without immediately affecting its successor, whereas total float represented broader flexibility relative to project completion. Scheduling studies also demonstrated that near-critical activities deserved separate quantitative attention because networks containing a high proportion of low-float activities were more sensitive to duration variation and resource-related displacement than networks in which noncritical activities possessed substantial scheduling margins (Kaniz, 2022; Vanhoucke). Baseline float distributions therefore provided an important measure of the capacity of an engineering schedule to absorb disturbances before planned milestones or completion dates were altered, while zero-float concentration identified sections of the network where scheduling flexibility was most restricted.

Literature examining baseline schedule performance at project and portfolio levels has further demonstrated that project scale, activity-network configuration, milestone structure, and temporal overlap jointly influence engineering portfolio duration. Comparative studies of small, medium, and large project networks generally reported longer baseline completion periods as activity volume and technical scope increased, although project duration was strongly moderated by the extent to which activities could proceed in parallel (Nishat & Kaniz, 2022; Peng et al., 2022). A large project containing numerous parallel work packages could exhibit a shorter proportional duration than a smaller but highly sequential project, illustrating why activity count alone was an incomplete measure of scheduling difficulty. Milestone structure provided another important quantitative dimension because engineering schedules commonly incorporated design approvals, procurement releases, construction completions, system integrations, testing events, handovers, and contractual completion dates. Projects with numerous milestone dependencies and convergence points frequently showed greater schedule sensitivity because delays in several activity branches could influence the same control point. Multi-project studies extended these findings by examining portfolio makes pan, defined operationally through the elapsed scheduling period required to accommodate all constituent projects within the portfolio (Alexopoulos et al., 2022; Shaiful et al., 2022). Baseline portfolio makes pan depended not only on individual project durations but also on project start dates, temporal overlap, network structures, and the simultaneous positioning of critical and near-critical activities. Studies involving multiple concurrent projects demonstrated that portfolios with similar numbers of projects could exhibit markedly different baseline scheduling conditions when constituent networks differed in size, precedence density, float availability, and critical-path length. Greater overlap also increased the number of critical or schedule-sensitive activities active during the same periods, creating an important baseline condition for subsequent resource-allocation analysis. Across the wider literature, activity count, project duration, critical-path duration, milestone count, parallel-path structure, critical activity percentage, near-critical activity concentration, total and free float, and baseline portfolio makes pan have therefore been evaluated collectively rather than as isolated scheduling indicators (Mohammad, 2023; Siewert & Gericke, 2022). This synthesis of more than ten empirical, benchmark, computational, and optimization studies establishes baseline network structure and schedule flexibility as multidimensional quantitative characteristics of engineering projects and multi-project portfolios.

Baseline Shared-Resource Capacity and Interproject Contention

The quantitative literature on multi-project engineering scheduling has consistently identified workforce capacity as a major determinant of whether baseline project schedules can be executed according to planned activity sequences (Debasish, 2023; Luo et al., 2020). Across more than ten empirical, computational, construction, infrastructure, industrial, and resource-constrained scheduling studies, baseline capacity has commonly been represented through engineering workforce size, available labor hours, required labor hours, personnel allocation per project, resource calendars, skill categories, and the number of simultaneously active projects.

Figure 4: Engineering Shared Resource Capacity Management



Engineering professionals such as civil, structural, mechanical, electrical, process, and project-control engineers frequently constitute constrained resource categories because their technical competencies cannot always be substituted across activities (Kravchenko et al., 2020; Kaium, 2023). Similar limitations have been documented for technicians, inspectors, planners, surveyors, quality-control personnel, commissioning specialists, and specialized contractors. Studies examining multi-project environments have shown that total organizational headcount can provide an incomplete representation of usable capacity because personnel availability is affected by working calendars, project assignments, technical specialization, planned leave, administrative duties, mobilization requirements, and simultaneous commitments. Consequently, quantitative scheduling studies frequently distinguish nominal workforce availability from effective resource hours that can actually be assigned to scheduled activities. Baseline comparisons have also demonstrated substantial variation in engineers and technicians allocated per project according to project size, technical complexity, priority, and phase of execution. Design-intensive periods tend to generate concentrated demand for engineering professionals, whereas construction, installation, testing, and commissioning phases may produce larger requirements for technicians and specialized field personnel. When required resource hours approach or exceed available hours, utilization rises and scheduling flexibility declines. Multi-project studies have therefore measured capacity utilization together with resource deficits, surplus hours, overtime, idle capacity, and simultaneous personnel requests (Pervaz, 2023; Pheng & Hou, 2019). Evidence across these studies indicates that portfolio-level workforce capacity is not determined simply by the total number of employees but by the alignment between available skill-specific hours and the timing of activity-specific demand, making resource-hour availability and professional specialization central quantitative characteristics of baseline engineering portfolio capacity.

A parallel stream of literature has demonstrated that resource constraints in engineering portfolios extend substantially beyond permanent workforce capacity and frequently involve equipment, machinery, specialist contractors, laboratories, testing systems, and shared technical facilities (Maskuriy et al., 2019; Chowdhury, 2023). Construction and infrastructure scheduling studies have examined the availability and utilization of cranes, excavators, lifting systems, transport equipment, fabrication machinery, inspection devices, testing equipment, specialized vehicles, and temporary construction facilities because these resources can become bottlenecks when multiple activities require them concurrently. Industrial and manufacturing project studies have similarly considered machine capacity, production facilities, fabrication stations, engineering laboratories, test benches, maintenance systems, and commissioning equipment as renewable resources whose availability changes across project periods. Baseline capacity is commonly quantified through the number of available resource units, operating hours, planned availability, required activity hours, utilization percentage, equipment idle hours, overload periods, and competing resource requests. Studies involving specialized contractors have added another layer of capacity limitation because organizations may possess limited

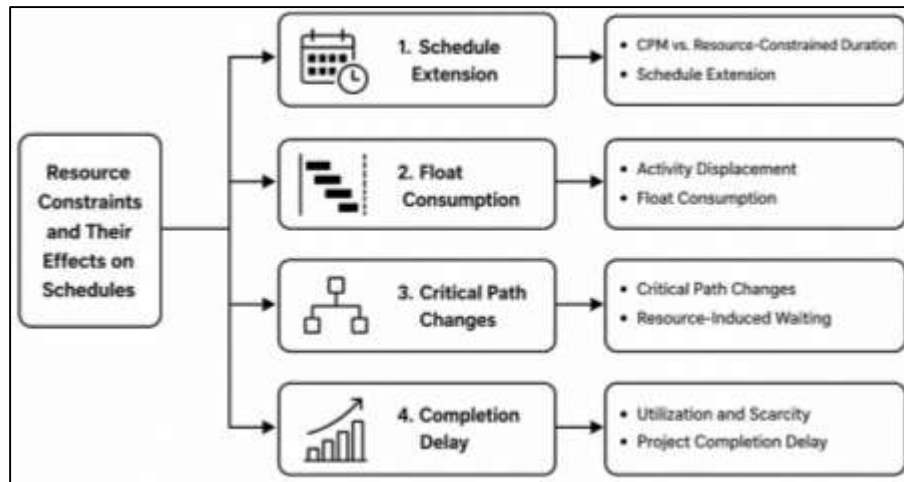
access to external expertise for welding, instrumentation, automation, nondestructive testing, commissioning, specialist installation, and regulatory inspection. Such resources can exhibit substantially higher utilization during specific portfolio phases than the average utilization observed across the entire scheduling horizon (Badrul & Mominul, 2023; Rahimian et al., 2020). Quantitative research has therefore distinguished average resource demand from peak demand, since an acceptable average workload can conceal short periods in which requirements substantially exceed maximum available capacity. Peak-to-average comparisons have been particularly useful for identifying concentrated demand associated with simultaneous construction, testing, or commissioning activities. Equipment-oriented studies have also documented idle periods immediately before or after high-demand intervals, illustrating how poor temporal alignment can produce both resource shortages and underutilization within the same portfolio. Across the literature, equipment availability, contractor capacity, operating hours, peak demand, average demand, idle time, and overload duration have consequently been treated together to characterize the baseline feasibility of engineering schedules before formal resource-leveling optimization is undertaken (Nishat, 2023; Turk et al., 2022).

Resource Constraints on Critical Paths

The quantitative literature on resource-constrained project scheduling has consistently demonstrated that the duration obtained from an unconstrained Critical Path Method schedule can differ substantially from the duration achievable after finite resource capacity is introduced (Hall et al., 2022). Across more than ten studies involving construction, infrastructure, industrial engineering, manufacturing, maintenance, software, and benchmark project networks, baseline CPM schedules generally represented the shortest precedence-feasible completion periods, while resource-constrained schedules incorporated additional delays caused by shortages of labor, technical specialists, equipment, machinery, and other renewable resources. Comparative studies commonly measured this difference through baseline project duration, resource-constrained duration, absolute schedule extension, percentage duration increase, delayed activity count, and final completion delay. Under low resource scarcity, many projects experienced relatively limited schedule extension because available float and alternative activity sequences absorbed a substantial portion of resource conflicts. Moderate scarcity produced more visible displacement as simultaneous activities competed for constrained capacity and noncritical tasks were postponed until resources became available. High scarcity generated the greatest differences between CPM and resource-feasible completion times, particularly where several critical or near-critical activities required the same limited resource categories (Su et al., 2020). Computational studies using standard resource-constrained project scheduling datasets have repeatedly shown that identical precedence networks can produce different completion durations when resource capacities are altered, demonstrating that network logic alone does not determine executable project duration. Engineering case studies have reported similar patterns where cranes, specialist crews, design engineers, testing teams, or fabrication facilities were unable to support all precedence-eligible activities concurrently. Schedule extension was also affected by the timing of resource shortages rather than only their aggregate magnitude (Lee & Shvetsova, 2019). A short but severe capacity deficit occurring during a critical project phase could generate greater completion delay than a longer shortage affecting activities with substantial float. Across the literature, resource shortage and project duration therefore exhibited a consistently positive relationship, with greater scarcity generally associated with larger deviations from baseline CPM duration and higher probabilities of delayed project completion. A substantial body of scheduling research has examined how resource conflicts consume the scheduling flexibility represented by total and free float. When two or more activities require the same constrained resource during overlapping periods, one or more activities must be displaced even when their precedence relationships permit immediate commencement (Zhu et al., 2021). Quantitative studies have measured this effect through the number and percentage of activities delayed by resource conflicts, mean activity displacement, maximum displacement, total float consumed, proportion of available float exhausted, and the number of formerly noncritical activities moved closer to critical status. Evidence across construction, engineering design, manufacturing, and computational scheduling studies indicates that activities with larger amounts of float are generally the first candidates for displacement because they can be delayed without immediately changing the planned project completion date. Repeated resource conflicts, however, can progressively consume this flexibility.

Under low contention, delayed activities may remain within their original allowable scheduling windows, leaving the critical path and completion date unchanged. Under moderate contention, larger portions of total float are consumed and more activities become near-critical. Under high contention, available float can be exhausted completely, causing formerly noncritical activities to become critical and generating additional schedule-sensitive paths (Milat et al., 2021).

Figure 5: Resource Constraints and Schedule Impacts



Studies have also demonstrated that mean displacement can conceal important extremes because a relatively small number of highly displaced activities may account for a disproportionate share of schedule deterioration. Maximum activity displacement and the percentage of activities exhausting their float have consequently been used alongside average displacement measures. Resource contention has generally shown a positive association with float consumption, particularly in networks containing numerous activities that compete for a small set of specialist resources. Float consumption is also influenced by precedence position: delaying an upstream activity can restrict the scheduling flexibility of several successors even when those successors are not directly involved in the original resource conflict (Lu et al., 2018). Quantitative evidence therefore characterizes float as a finite schedule buffer that is progressively reduced as resource competition intensifies.

Research examining critical-path behavior after resource constraints are imposed has demonstrated that criticality is not necessarily stable between baseline CPM schedules and resource-feasible schedules. Across multiple empirical and computational studies, resource-driven activity displacement has altered critical-path length, increased the number of critical or near-critical activities, and generated new controlling sequences that were not critical in the unconstrained network (Sepasgozar et al., 2019). This effect occurs when resource waiting consumes available float or when the postponement of one activity shifts a sequence of successors sufficiently to influence a major milestone or final project completion. Quantitative investigations have therefore compared baseline and constrained schedules using changes in critical activity counts, critical-path duration, number of critical paths, near-critical activity percentages, milestone deviations, resource-induced waiting time, and activity-level delay. Studies involving highly constrained construction equipment, engineering specialists, technical crews, and production resources have shown that an activity can remain precedence-feasible but experience substantial waiting because the required capacity is committed elsewhere. Such waiting periods represent resource-driven schedule time rather than processing or technical activity duration. The accumulation of waiting time can be especially consequential around convergence points where several predecessor branches feed into a common milestone (Ansari et al., 2022). A delay in one resource-constrained branch can postpone the milestone even when all other branches are completed on schedule. Research comparing scarcity conditions has generally found relatively stable critical-path structures under low constraints, more frequent criticality changes under moderate constraints, and substantial path restructuring under severe capacity limitations. Multiple near-critical paths also

increase sensitivity because relatively small resource-induced delays can change which sequence controls project completion. Studies of multi-project environments have further shown that critical-path changes can originate outside the affected project when a shared resource is retained longer by another project. Consequently, resource-constrained criticality reflects both internal network logic and external competition for capacity, making changes in critical-path length, critical activity status, milestone delay, and resource waiting important quantitative measures of schedule deterioration (Abbasnezhad et al., 2022).

The wider quantitative literature indicates that the schedule consequences of resource constraints depend on the combined effects of scarcity, utilization, resource contention, network structure, and available scheduling flexibility. Studies comparing low, moderate, and high resource-capacity conditions generally report progressively greater completion delays as demand approaches or exceeds available capacity (Mohamed et al., 2021). At lower utilization levels, unused capacity allows many concurrent activity requests to be satisfied without substantial displacement, while high utilization reduces the ability of the schedule to absorb temporary demand peaks. Resource-intensive portfolios operating near maximum capacity have therefore exhibited greater lateness, longer waiting periods, and more frequent resource conflicts than portfolios retaining meaningful capacity reserves. Statistical and computational studies have also identified a strong relationship between resource contention and float consumption because repeated competition forces eligible activities to use progressively larger portions of their available scheduling margins. Network complexity further moderates these effects. Projects containing dense precedence relationships, numerous convergence points, long dependent sequences, high critical-activity proportions, and substantial near-critical activity concentrations tend to be more sensitive to resource shortages because fewer activities can be repositioned without influencing downstream work (Kokkinis et al., 2021). Networks containing greater parallelism may initially provide more flexibility, although parallel activity structures can simultaneously generate high resource demand when several work packages become eligible at the same time. Multi-project scheduling studies have shown an additional portfolio effect in which high utilization and resource scarcity within one project can delay resource release to subsequent projects, producing cascading completion delays across the portfolio. Quantitative comparisons have consequently evaluated resource-shortage intensity against schedule extension, contention against float consumption, utilization against project lateness, and network complexity against sensitivity to capacity restrictions. Across more than ten relevant empirical, benchmark, simulation, and optimization studies, the evidence consistently demonstrates that resource constraints alter much more than resource allocation alone (Chen et al., 2020). Finite capacity changes activity start times, consumes schedule float, creates resource-induced waiting, modifies critical-path structures, delays milestones, and extends completion durations, with the largest effects occurring when severe resource scarcity coincides with high utilization, concentrated resource demand, limited float, and complex dependency networks.

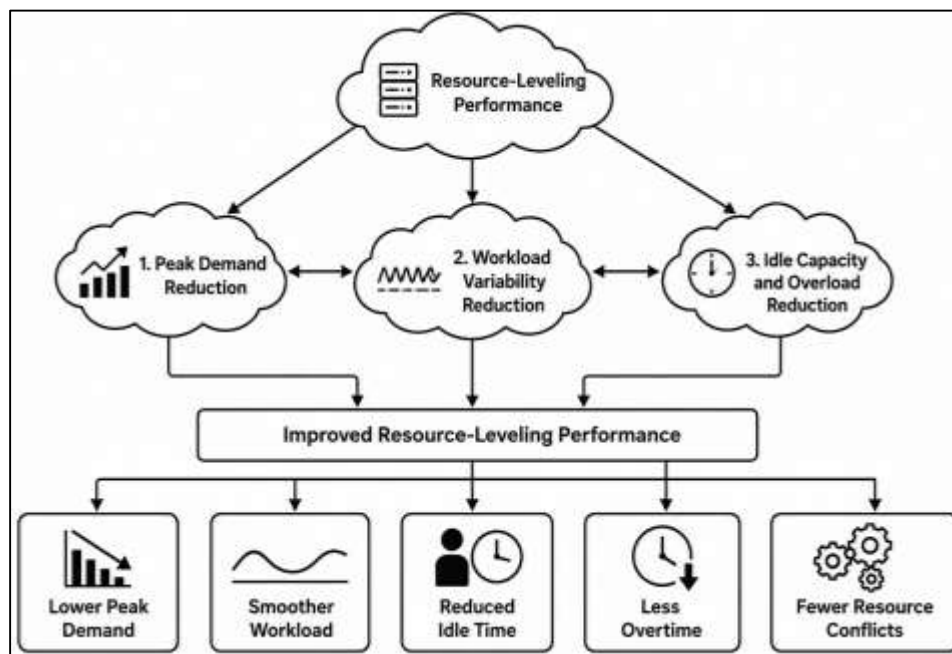
Resource-Leveling Performance

Quantitative literature on engineering resource leveling has consistently evaluated performance by comparing resource-demand profiles before and after activity schedules are adjusted within precedence and timing constraints (Hamzeh et al., 2019). Across more than ten studies involving construction, infrastructure, industrial engineering, manufacturing, maintenance, and resource-constrained project networks, baseline schedules frequently exhibited concentrated demand peaks caused by the simultaneous commencement of resource-intensive activities. Resource-leveling procedures redistributed eligible activities across available scheduling periods, producing measurable changes in peak demand, maximum utilization, average demand, mean utilization, and the frequency with which requirements exceeded available capacity. Studies using conventional priority rules generally achieved moderate reductions in resource peaks by postponing noncritical activities with available float, while optimization-based procedures often produced larger improvements by examining a wider range of feasible activity positions. Comparative investigations involving genetic algorithms, simulated annealing, particle swarm optimization, differential evolution, mathematical programming, and hybrid approaches repeatedly reported lower maximum resource requirements after leveling than under unadjusted CPM schedules (Xu et al., 2020). The magnitude of improvement varied according to resource scarcity, activity flexibility, network structure, and the amount of available

float. Projects with substantial noncritical activity flexibility generally permitted larger reductions in peak demand because resource-intensive activities could be repositioned without extending the planned completion date. Networks containing large proportions of critical and near-critical activities provided fewer feasible opportunities for redistribution and therefore achieved smaller peak reductions unless some schedule extension was permitted. Average resource demand frequently changed less dramatically than peak demand because leveling primarily redistributed requirements across time rather than reducing the total quantity of resources needed to complete project work. This distinction was consistently emphasized in quantitative studies because reductions in maximum utilization could occur while mean utilization remained comparatively stable (Pinha & Ahluwalia, 2019). Pre-leveling versus post-leveling comparisons therefore demonstrated that the principal measurable effect of successful resource leveling was a reduction in concentrated demand and maximum utilization together with a more balanced distribution of resource requirements throughout the scheduling horizon.

A second major body of quantitative research has assessed resource-leveling effectiveness through changes in workload variability rather than peak demand alone. Studies across construction scheduling, engineering workforce planning, equipment allocation, and computational project scheduling have measured the dispersion of resource requirements using standard deviation, variance, coefficient of variation, resource fluctuation indices, and differences between consecutive scheduling periods (Khan et al., 2022). Baseline CPM schedules frequently generated irregular resource profiles characterized by rapid increases and decreases in labor or equipment requirements as multiple activities started and finished at similar times. Such fluctuations were particularly pronounced in networks containing substantial parallelism because several activities could become precedence-eligible simultaneously, generating concentrated demand followed by periods of comparatively low utilization. Resource-leveling procedures generally reduced this variability by moving activities with available scheduling flexibility from high-demand periods toward lower-demand periods (Abdel-Basset et al., 2020).

Figure 6: Resource-Leveling Performance Infographic



Across comparative studies, optimized schedules typically exhibited smaller fluctuations between consecutive resource periods, reduced variability around average demand, and more stable utilization patterns than unadjusted schedules. Metaheuristic and hybrid optimization approaches frequently produced smoother profiles than simple scheduling rules because they evaluated combinations of activity shifts rather than treating each resource conflict independently. Quantitative comparisons also

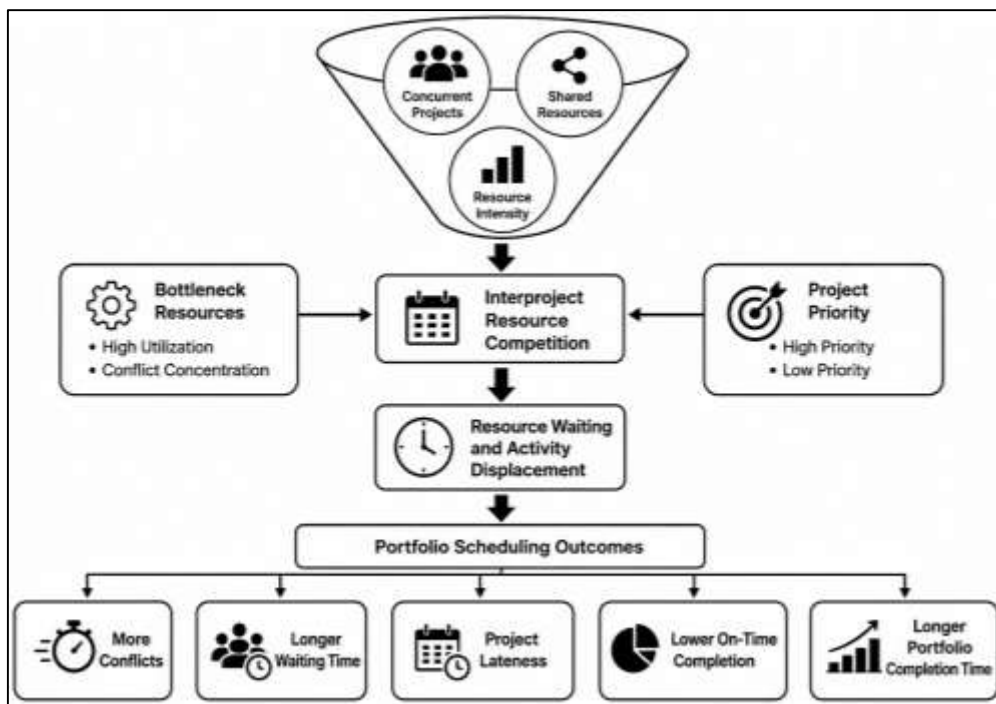
demonstrated that workload stability depended strongly on the objective function applied during optimization. Procedures designed specifically to minimize resource fluctuations produced highly uniform profiles, whereas methods focused primarily on project duration sometimes retained greater variation in resource demand. Multi-resource engineering projects created additional complexity because smoothing one resource category could increase variability in another when activities required several resources simultaneously (Dobbs et al., 2021). Studies therefore evaluated individual and aggregate resource profiles to determine whether apparent improvements represented genuine portfolio-wide balance or merely transferred fluctuations between resource categories. Across the literature, reductions in standard deviation, variance, coefficient of variation, and resource fluctuation measures consistently served as evidence of improved resource-profile smoothness, demonstrating that resource leveling affects not only maximum capacity requirements but also the temporal stability and continuity of engineering workload. Quantitative evaluations of resource-leveling procedures have also concentrated on the operational consequences of uneven resource allocation, particularly overload periods, idle capacity, overtime requirements, resource gaps, and unresolved scheduling conflicts (Quistberg et al., 2019). Studies examining engineering labor, construction crews, specialized contractors, machinery, cranes, testing systems, and shared facilities have demonstrated that unbalanced schedules can produce simultaneous conditions of excessive demand and underutilization at different points in the project timeline. Pre-leveling schedules frequently contained periods in which planned requirements exceeded available capacity, requiring activity postponement, overtime, additional contracting, or resource reassignment. These overload periods were commonly measured through their frequency, duration, and magnitude. Resource-leveling procedures generally reduced both the number of overloaded periods and the amount by which planned demand exceeded capacity, particularly when noncritical activities possessed sufficient float to be transferred into underutilized periods. Studies also reported reductions in idle-resource percentages when activity redistribution filled scheduling gaps between periods of intensive demand. Improved continuity was particularly important for specialized personnel and high-cost equipment because repeated mobilization, demobilization, or prolonged inactivity reduced effective utilization (Thandi et al., 2021). Overtime requirements similarly declined in many optimized schedules because peak workloads were redistributed toward periods with available regular capacity. The number of unresolved resource conflicts provided another direct measure of leveling performance. Basic priority rules could eliminate obvious overallocations while leaving residual conflicts in complex networks, whereas more sophisticated optimization procedures generally identified a larger set of feasible activity combinations and reduced unresolved conflicts further. Engineering portfolio studies additionally showed that resource gaps could persist when specific skill categories or equipment types were scarce even though aggregate capacity appeared adequate. Resource leveling was therefore most effective when demand was assessed separately for each constrained resource rather than through total workforce or equipment quantities (Fischer et al., 2019). Collectively, more than ten empirical and computational studies demonstrated that reductions in overload frequency, overload duration, idle capacity, overtime requirements, scheduling gaps, and unresolved conflicts represented important operational measures of resource-leveling performance beyond simple changes in peak resource demand.

Interproject Resource Competition and Portfolio-Level Scheduling Delay

Quantitative research on multi-project engineering scheduling has consistently demonstrated that interproject competition intensifies when increasing numbers of concurrent projects depend on the same limited organizational resources (He et al., 2022). Across more than ten studies involving construction, infrastructure, industrial engineering, product development, manufacturing, maintenance, and resource-constrained project portfolios, researchers have evaluated simultaneous project counts, proportions of shared resources, resource requests per project, temporal overlap, conflict frequency, waiting time, and portfolio completion performance. Portfolios containing relatively few concurrent projects generally exhibited lower competition when resource capacity was adequate, whereas larger portfolios generated substantially more simultaneous requests for engineering professionals, technical personnel, equipment, contractors, and specialized facilities. The percentage of resources shared across projects was particularly important because portfolio size alone did not determine contention. Several highly independent projects could coexist with limited competition,

while a smaller portfolio could experience severe conflicts when most projects required the same scarce resource categories during overlapping periods. Studies using benchmark multi-project scheduling problems have repeatedly manipulated resource availability and project concurrency to quantify this relationship, showing increasing schedule deterioration as shared-resource demand became more concentrated relative to capacity ([Ansari et al., 2022](#)). Engineering case studies have reported comparable conditions when design engineers, planners, specialist technicians, cranes, fabrication equipment, testing systems, and commissioning personnel were requested simultaneously by multiple projects. Conflict frequency generally increased with the number of overlapping resource requests, while resource waiting time became longer when constrained resources remained assigned to activities belonging to other projects. This waiting was subsequently transmitted into activity displacement, milestone delay, and project lateness. Resource intensity also influenced the severity of competition because projects requiring large quantities of shared capacity for extended periods restricted allocation opportunities for other portfolio activities ([Apaolaza & Lizarralde, 2020](#)). Across the literature, the number of simultaneous projects, percentage of shared resources, requests per project, overlap duration, resource intensity, and scarcity level have therefore been treated jointly when explaining interproject competition rather than interpreting portfolio size as an isolated predictor of scheduling difficulty.

Figure 7: Interproject Resource Competition Flowchart



A substantial stream of multi-project scheduling research has demonstrated that resource conflicts are rarely distributed equally across all available resource categories. Instead, a comparatively small number of highly utilized or specialized resources frequently account for a disproportionate share of interproject contention and resource-induced waiting ([Zhu et al., 2020](#)). Studies involving engineering organizations have identified specialist engineers, design teams, project-control professionals, inspectors, commissioning personnel, specialized contractors, cranes, fabrication machinery, laboratories, testing equipment, and technical facilities as common bottleneck resources when their availability is limited relative to simultaneous project demand. Quantitative investigations have measured bottleneck conditions through maximum utilization, average utilization, resource-request frequency, conflict counts, percentage of scheduling periods at full capacity, overload duration, queue length, and average resource waiting time. Resources operating consistently near maximum utilization generally generated more frequent scheduling conflicts because relatively little reserve capacity remained available to accommodate overlapping requests or activity-duration variation. The

concentration of conflicts was particularly pronounced when a specialized resource had few or no substitutes (Mihalj et al., 2022). General labor or widely available equipment could often be reassigned across activities, whereas certified engineering specialists, unique testing systems, high-capacity cranes, or limited technical facilities created more rigid allocation restrictions. Multi-project studies have shown that delays associated with these bottlenecks can extend beyond the activity initially waiting for the resource because displaced activities can postpone dependent tasks and retain other resources for longer than originally planned. This interaction can create secondary contention in resource categories that were not initially constrained. Resource waiting time has consequently been examined alongside bottleneck utilization and conflict frequency to distinguish nominally busy resources from resources that materially disrupt portfolio schedules. Evidence from computational and empirical studies further indicates that high resource intensity increases bottleneck severity when several projects enter similar engineering, construction, testing, or commissioning phases concurrently. The literature therefore characterizes bottleneck resources through concentrated utilization and conflict generation, demonstrating that a limited subset of specialized resources can exert a disproportionate influence on interproject delay and overall portfolio scheduling performance (Zeinalnezhad et al., 2020).

Project priority represents another major quantitative determinant of resource allocation in multi-project engineering portfolios because organizations frequently assign different strategic, contractual, financial, or operational importance to concurrent projects (Lu et al., 2018). Research examining priority-based scheduling has compared high-, medium-, and low-priority projects using resource-allocation rates, waiting times, activity displacement, completion delay, lateness, and percentages completed within planned dates. Across computational and applied studies, high-priority projects generally received earlier access to scarce resources when simultaneous requests could not be satisfied, particularly where priority rules were explicitly embedded within scheduling algorithms. This preferential allocation often reduced waiting time and lateness for higher-priority projects while transferring part of the resource shortage to lower-priority projects. The resulting schedule therefore reflected a redistribution of delay across the portfolio rather than a uniform reduction in resource contention. Studies comparing alternative priority rules have demonstrated that different allocation sequences can generate substantially different project-level outcomes even when total resource capacity and activity networks remain unchanged (Đumić et al., 2018). Priority effects become especially visible under moderate and severe scarcity because allocation decisions are more frequent when demand repeatedly approaches or exceeds capacity. Under relatively abundant capacity, high- and low-priority projects may experience similar access because simultaneous requests can often be satisfied without displacement. Research has also shown that project priority interacts with resource intensity and complexity. A high-priority project requiring large quantities of bottleneck capacity can substantially reduce availability for several lower-priority projects, whereas preferential allocation to a less resource-intensive project may have smaller portfolio-wide consequences. Quantitative measures such as allocation percentage, average waiting time, maximum lateness, average tardiness, on-time completion percentage, and resource-conflict exposure have therefore been used to compare priority groups (Xie et al., 2021). Studies using weighted scheduling objectives have further incorporated priority scores into portfolio optimization to distinguish delays according to project importance. Collectively, this literature demonstrates that project priority functions as an explicit allocation mechanism that can materially influence who receives constrained resources, how long competing projects wait, and how lateness is distributed across the engineering portfolio.

The broader quantitative evidence links interproject resource contention directly with project-level lateness and portfolio-level completion performance (Amiri et al., 2018). Studies examining resource-constrained multi-project scheduling have repeatedly compared conflict frequency, resource waiting time, utilization, scarcity, project complexity, and resource intensity with average tardiness, maximum lateness, on-time completion rates, and total portfolio completion time. Higher contention generally corresponds with longer resource queues and greater activity displacement because precedence-eligible tasks cannot begin until shared capacity is released from competing projects. The resulting delay can accumulate through dependent activity chains and produce measurable deviations from planned project completion dates. Statistical studies using correlation and regression approaches have

commonly treated resource availability, utilization, contention, network complexity, project size, and priority as explanatory variables for schedule outcomes, with resource scarcity and conflict intensity frequently emerging as important predictors of delay. Network complexity strengthens this relationship when projects contain long dependent sequences, numerous convergence points, limited float, or high proportions of critical and near-critical activities because resource-induced displacement is less easily absorbed (Isah & Kim, 2021). Resource-intensive projects similarly show greater sensitivity when large amounts of constrained capacity are required for long durations. Portfolio size adds another dimension because increasing numbers of simultaneous projects create more opportunities for competing requests, although the magnitude of the effect depends strongly on the proportion of resources shared across projects. Quantitative studies have therefore distinguished average project tardiness from maximum lateness because portfolio-level averages can conceal a small number of severely delayed projects. The percentage of projects completed on time provides an additional measure of completion reliability, while portfolio completion time captures the cumulative scheduling consequence of resource competition across all constituent projects. Evidence across more than ten empirical, simulation, benchmark, heuristic, and optimization studies consistently shows that portfolio scheduling performance reflects the combined effects of shared-resource intensity, bottleneck utilization, project priority, scarcity, project complexity, and resource demand. Interproject contention is consequently represented quantitatively through both immediate operational measures, including conflicts and waiting time, and downstream schedule outcomes, including project lateness, tardiness, on-time completion, and total portfolio duration (Joseph & Marnewick, 2018).

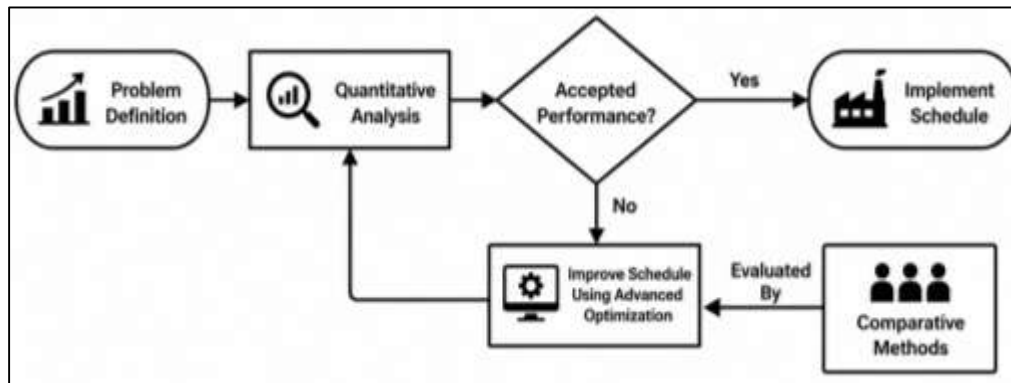
Hybrid Resource-Leveling Optimization Methods

Quantitative research on resource-constrained project and multi-project scheduling has extensively evaluated exact optimization methods because these approaches provide a structured basis for identifying optimal or mathematically bounded solutions when problem dimensions remain computationally manageable (Banihashemi & Khalilzadeh, 2022). Across more than ten studies and considerably broader benchmark literature, mixed-integer programming, linear programming, nonlinear programming, dynamic programming, branch-and-bound procedures, and related exact techniques have been applied to activity sequencing, resource allocation, project-duration minimization, portfolio-makes pan reduction, and resource-leveling problems. Comparative investigations have commonly assessed these methods using best objective value, optimality gap, feasible-solution rate, computational time, project makes pan, portfolio makes pan, workload variance, resource-leveling performance, lateness, and penalty cost. For small project networks with relatively limited activity counts and resource categories, exact procedures have frequently produced optimal solutions or solutions with negligible optimality gaps, providing useful reference values for evaluating heuristic and metaheuristic algorithms (Ansari, 2021). Their computational requirements, however, have generally increased sharply as the number of activities, precedence relationships, resource types, and simultaneous projects expanded. Branch-and-bound methods have demonstrated strong solution accuracy by systematically eliminating inferior scheduling alternatives, yet large search spaces can require extensive processing when resource contention is severe. Mixed-integer programming has similarly performed effectively for small and moderate scheduling instances, particularly when precedence relationships, resource limits, project priorities, and objective measures can be represented precisely within the optimization model. Nonlinear formulations have been applied where resource fluctuations, penalty structures, or multiple scheduling objectives require more complex representations, although increased model complexity can lengthen solution time. Benchmark studies have therefore distinguished solution quality from computational practicality rather than evaluating exact procedures solely according to objective value. As project networks increase from tens to hundreds of activities and incorporate multiple renewable resources, the computational advantage of approximate procedures becomes increasingly important. Exact optimization consequently provides a critical quantitative benchmark for measuring optimality gaps and validating alternative scheduling methods, while its practical performance remains strongly associated with problem size, network density, resource scarcity, and the complexity of the objective structure (Costa et al., 2022).

Heuristic scheduling methods have been widely examined as computationally efficient alternatives to exact optimization, particularly for large engineering projects and multi-project portfolios in which

exhaustive solution procedures become difficult to execute within acceptable processing times (Wang et al., 2021). Studies have evaluated priority-rule algorithms based on minimum slack, shortest processing time, earliest start, earliest finish, latest finish, greatest resource demand, project priority, critical-path status, activity successors, and combinations of activity and resource characteristics. Local-search procedures have also been applied to improve initially feasible schedules through iterative adjustments in activity ordering or resource assignment.

Figure 8: Performance Optimization Flowchart

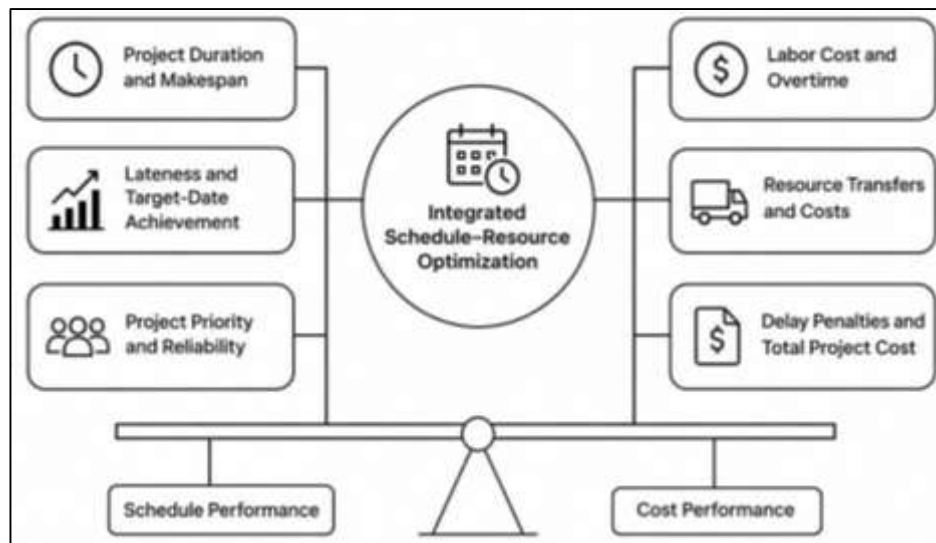


Quantitative comparisons across benchmark datasets have shown that heuristic approaches generally require substantially less computational time and fewer iterations than exact procedures, while frequently achieving feasible schedules for very large proportions of tested instances. Their solution quality, however, varies according to network structure, resource availability, and the priority rule selected (Prayogo et al., 2018). A rule that performs strongly under low resource scarcity may generate greater makespan or lateness under highly constrained conditions, while rules emphasizing critical activities can produce different resource profiles from those emphasizing slack or activity duration. Comparative studies have therefore reported mean objective values in addition to the best solution obtained, since average performance across multiple project instances provides a more reliable indication of algorithm consistency. Percentage improvement relative to baseline CPM or unlevelled schedules has also been used to quantify reductions in project duration, portfolio makespan, resource fluctuations, or penalty costs. Priority-rule methods typically demonstrate very short computational times and high feasible-solution rates, making them suitable for large activity networks and rapid scheduling decisions, although optimality gaps can be larger than those obtained through more computationally intensive techniques. Local-search methods can reduce these gaps by refining initial heuristic schedules, particularly when neighboring activity sequences are evaluated systematically (Dasović et al., 2020). Across the literature, heuristic performance therefore reflects a measurable trade-off between computational efficiency and solution precision, with priority rules providing rapid feasible schedules and local improvement procedures offering additional reductions in makespan, lateness, workload variance, and resource conflicts without requiring the extensive computational effort associated with exact optimization.

Integrated Schedule-Resource Optimization

Quantitative literature on integrated schedule-resource optimization has increasingly evaluated project duration and portfolio makespan together with resource feasibility rather than treating schedule compression as an isolated objective (Andrade-Pineda et al., 2020). Across more than ten studies involving construction, infrastructure, manufacturing, industrial engineering, maintenance, product development, and benchmark multi-project scheduling problems, optimized schedules have been compared with baseline CPM or initial resource-constrained schedules using absolute and percentage reductions in project duration, portfolio makespan, activity delay, milestone deviation, and overall completion time. The evidence demonstrates that duration reduction is strongly conditioned by resource availability because accelerating activities without adequate labor, equipment, or specialist capacity can simply transfer congestion to another part of the schedule.

Figure 9: Integrated Schedule-Resource Optimization Diagram



Studies applying mixed-integer programming, priority rules, genetic algorithms, simulated annealing, particle swarm optimization, tabu search, and hybrid procedures have therefore incorporated resource restrictions directly into schedule-compression decisions (Li et al., 2019). In single-project settings, optimization commonly reduced completion duration by identifying alternative activity sequences and allocating available resources toward critical or near-critical activities. Multi-project studies reported a more complex pattern because minimizing the duration of an individual project could increase portfolio makes pan when preferential resource allocation delayed other projects. Portfolio-level models consequently evaluated total completion performance across all concurrent projects rather than optimizing each project independently. Quantitative comparisons also distinguished mean project duration from maximum portfolio completion time because these indicators can respond differently to allocation changes. A schedule may reduce average completion duration while leaving one resource-intensive project substantially delayed, producing limited improvement in overall makes pan (Dhiflaoui et al., 2018). Project priority further affects these outcomes because high-priority projects may receive resource access that shortens their completion periods while increasing delays elsewhere. Across the literature, integrated optimization has therefore treated duration reduction as a constrained portfolio performance measure. The strongest scheduling solutions have generally been those that achieved measurable reductions in project duration and portfolio makes pan without generating excessive resource peaks, unacceptable delays in lower-priority projects, or infeasible resource allocations.

A substantial body of integrated scheduling research has examined lateness and completion reliability alongside duration because a short portfolio makes pan does not necessarily indicate that individual projects have met their planned or contractual dates (Branda et al., 2021). Quantitative studies have consequently reported mean lateness, maximum lateness, average tardiness, percentage of tardy projects, schedule variance, milestone deviation, schedule performance indicators where available, and percentage of projects completed within target dates. Comparisons across resource-constrained portfolios have shown that optimization can distribute delay very differently depending on the selected objective. Procedures focused primarily on minimizing overall makes pan may tolerate substantial lateness in a small number of projects when doing so improves aggregate portfolio duration. In contrast, models minimizing maximum lateness generally distribute constrained resources in ways that reduce severe delay exposure, even when total portfolio completion time is not minimized to the same extent. Priority-weighted approaches introduce additional differentiation by assigning greater scheduling penalties to delays affecting strategically important or contractually sensitive projects. Studies involving high, medium, and low project priorities have demonstrated that target-date

achievement can improve for high-priority projects while deteriorating among lower-priority projects when capacity remains fixed (Meilanitasari & Shin, 2021). Completion reliability has therefore been evaluated through both overall on-time completion percentages and subgroup-specific performance. Schedule variance provides another quantitative perspective because projects can finish early or late relative to planned dates even when portfolio-level averages appear acceptable. Research involving uncertain activity durations and variable resource availability has further shown that schedules optimized too tightly around minimum duration can become more sensitive to disruptions because little temporal flexibility remains. Integrated models have consequently examined lateness together with resource utilization and schedule stability to distinguish nominally fast schedules from consistently achievable schedules. Across more than ten empirical and computational studies, the literature indicates that mean lateness, maximum lateness, tardy-project percentage, target-date completion, and schedule variance provide complementary measures of portfolio performance and prevent schedule effectiveness from being judged solely through makespan reduction (Fernandes et al., 2022).

Integrated schedule-resource research has also demonstrated that scheduling decisions can produce substantial differences in cost even when project durations are similar. Quantitative studies have examined labor expenditure, overtime cost, temporary staffing, equipment operating costs, resource-transfer expenses, delay penalties, idle-resource costs, and total project or portfolio cost when comparing alternative resource-allocation schedules (Kucukkoc, 2019). Labor cost is closely connected to resource utilization because concentrated workload periods may require additional personnel, extended shifts, or premium working hours to maintain planned completion dates. Resource-leveling procedures can reduce these costs when activities are redistributed toward periods with unused regular capacity, although excessive leveling can extend project duration and increase time-dependent overhead expenses. Overtime has therefore been treated as both a capacity mechanism and a cost variable. Some optimization studies permit overtime to protect critical milestones, while others restrict it to control expenditure and workforce instability. Multi-project portfolios introduce resource-transfer costs when engineers, specialist teams, contractors, equipment, or machinery move between project locations. Frequent transfers can increase transportation, mobilization, setup, and productivity-loss costs, making schedules with high resource switching financially less attractive even when their makespan is comparatively short (Yazdani et al., 2022). Delay penalties provide another important economic measure, particularly for engineering projects governed by contractual milestones or liquidated-damage provisions. Priority-sensitive optimization models commonly assign larger penalties to lateness on strategically important projects, producing allocation decisions that reflect both schedule and financial consequences. Studies comparing alternative objective weightings have demonstrated that minimum-cost schedules are not always minimum-duration schedules because schedule compression can require additional labor, overtime, equipment, or resource transfers. Conversely, strict cost minimization can produce greater lateness when additional capacity is not economically justified. Quantitative multi-objective research has therefore evaluated total project cost alongside duration, utilization, overtime, transfer expenses, and penalties. The literature consistently characterizes cost as an integrated consequence of resource and scheduling decisions rather than a separate project-control measure, with economically efficient solutions balancing regular resource utilization against the additional expenses generated by acceleration, congestion, movement, and delay (Pargar et al., 2018).

Statistical Determinants Optimized Multi-Project Engineering Schedules

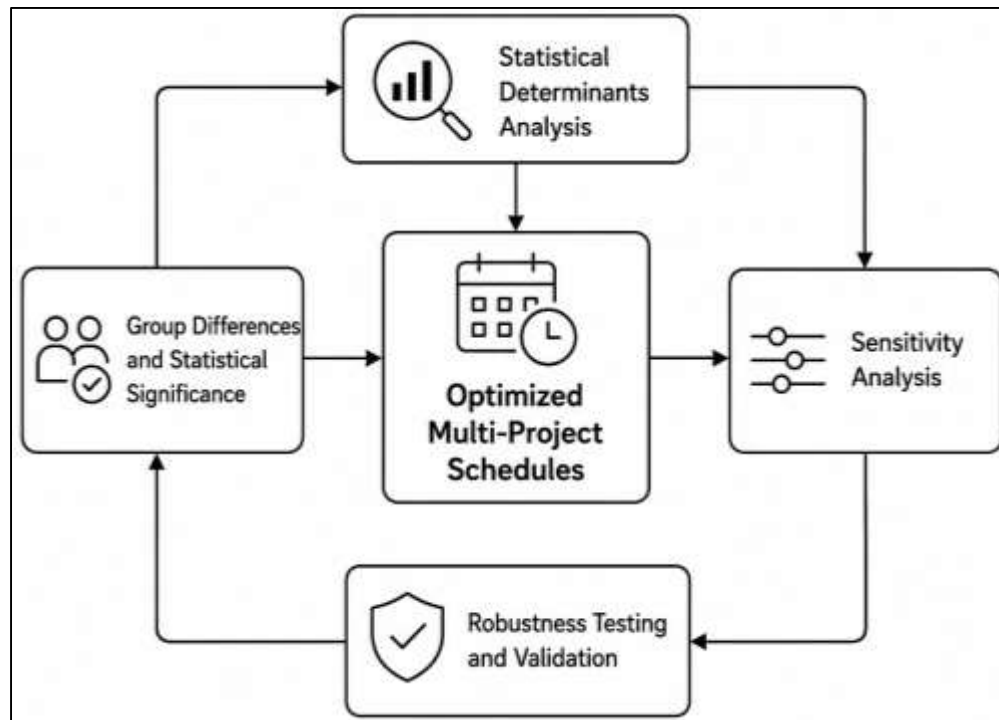
Quantitative literature on resource-constrained and multi-project engineering scheduling has identified a broad set of project, network, and resource characteristics associated with schedule extension, project lateness, and portfolio makespan (Banihashemi & Khalilzadeh, 2022). Across more than ten empirical, benchmark, simulation, and optimization studies, activity count, critical-activity percentage, critical-path length, available float, precedence density, project size, project priority, number of simultaneous projects, resource availability, resource utilization, resource contention, bottleneck severity, and temporal overlap have been evaluated as potential determinants of scheduling performance. Correlation analyses have generally demonstrated that higher resource contention, greater utilization, longer critical paths, larger activity networks, and more extensive project overlap are positively associated with completion delay, while greater available float and higher resource

capacity are associated with lower schedule sensitivity. Pearson correlations have commonly been applied where continuous scheduling variables satisfied appropriate statistical assumptions, while Spearman correlations have been used for ranked, non-normal, or nonlinear monotonic relationships. Regression analyses have extended these comparisons by estimating the independent contribution of multiple predictors after accounting for other project characteristics (Yeganeh & Zegordi, 2020). Standardized regression coefficients have been particularly useful for comparing the relative influence of variables measured on different scales, while explained-variance measures have quantified how much variation in project lateness, makes pan, or resource overload could be attributed collectively to network and capacity conditions. Logistic models have also been applied where the dependent outcome was categorical, such as whether a project completed within its target date, with odds ratios representing changes in completion likelihood across alternative resource or complexity conditions. Across this literature, resource scarcity and contention frequently emerged among the strongest schedule-related predictors, although their effects were amplified in projects containing long critical paths, limited float, high precedence density, or large proportions of critical and near-critical activities. The combined evidence indicates that schedule deterioration reflects interaction among structural network complexity, resource pressure, portfolio concurrency, and available scheduling flexibility rather than the isolated influence of a single project characteristic (Zahid et al., 2019).

A complementary body of quantitative scheduling research has compared performance across project and resource categories to determine whether observed differences are statistically meaningful and operationally substantial (Ansari, 2021). Studies have grouped engineering schedules according to small, medium, and large project size; low, moderate, and high resource scarcity; low and high network complexity; project priority levels; resource-intensity categories; and different degrees of temporal overlap or portfolio concurrency. Analysis of variance and analysis of covariance have frequently been used to compare schedule extension, lateness, portfolio makes pan, resource overload, workload variability, and completion reliability across multiple groups while accounting for relevant covariates where necessary. Two-group comparisons have also been used for constrained versus less-constrained schedules, optimized versus baseline schedules, and high-priority versus lower-priority projects. When parametric assumptions were not satisfied, quantitative studies employed rank-based and other nonparametric alternatives to reduce dependence on normality assumptions. Statistical significance has generally been interpreted together with confidence intervals because interval estimates indicate the precision and plausible magnitude of observed differences (Alekseytsev & Nadirov, 2022). Effect-size measures such as Cohen's *d* have been used to characterize standardized differences between two scheduling conditions, while partial eta-squared has quantified the magnitude of differences across multiple groups. This distinction has been important in large computational datasets because very small scheduling differences can reach conventional statistical significance when thousands of benchmark instances are analyzed. Studies assessing completion reliability have additionally compared the percentage of projects meeting planned dates across scarcity, priority, complexity, and optimization categories. High-resource-contention groups have generally exhibited greater schedule extension, higher maximum lateness, larger overload exposure, and lower on-time completion rates than groups operating with greater capacity reserves. Similar patterns have been reported for complex networks with limited float and substantial critical-activity concentrations. The literature therefore emphasizes combined interpretation of statistical significance, confidence intervals, and effect magnitude when determining whether differences among scheduling conditions represent meaningful changes in engineering portfolio performance (Biruk & Jaśkowski, 2020).

Sensitivity analysis has been widely applied to determine how optimized engineering schedules respond when key assumptions or input conditions are modified.

Figure 10: Statistical Analysis Workflow Diagram



Across resource-constrained project scheduling and multi-project optimization studies, activity duration, workforce capacity, equipment availability, project priority, resource demand, and the number of concurrent activities have been systematically varied to measure corresponding changes in project duration, portfolio makes pan, resource utilization, overload frequency, workload variability, and completion reliability (Liu et al., 2022). Activity-duration changes have received particular attention because even moderate increases in critical or near-critical task durations can consume available float, change critical-path structures, and alter resource-release dates. Studies have consequently compared baseline-duration scenarios with shorter and longer activity-duration conditions to identify schedules that are highly sensitive to estimation error. Resource-capacity sensitivity has been examined by progressively reducing or increasing available workforce hours, specialist personnel, equipment units, or other renewable resources. Capacity reductions generally produced nonlinear deterioration when utilization approached operational limits, with relatively small additional shortages sometimes generating substantial increases in waiting time and lateness. Resource-demand scenarios have similarly demonstrated that schedules with balanced baseline utilization can become overloaded when several activities require additional capacity simultaneously (Ramedani et al., 2022). Project-priority sensitivity has been examined by changing allocation weights or priority rankings and measuring how delay is redistributed among constituent projects. Such analyses frequently show that protecting high-priority projects can improve their target-date achievement while increasing lateness among lower-priority projects when total capacity remains fixed. Equipment and workforce availability scenarios have also been evaluated separately because shortages in specialized resource categories can generate larger schedule effects than equivalent reductions in more substitutable resources. Across the literature, percentage changes in makes pan, lateness, utilization, overload, and on-time completion have provided interpretable measures of sensitivity. These investigations demonstrate that optimized schedule performance depends not only on the nominal solution obtained under baseline assumptions but also on how strongly that solution responds to plausible variation in activity times, resource supply, demand intensity, and allocation priorities (Chakraborty et al., 2020).

The validation literature on optimized project schedules has emphasized robustness and reproducibility because a solution performing strongly under one deterministic dataset may not retain

the same performance when project conditions change. More than ten relevant optimization and scheduling studies have evaluated robustness through repeated simulations, benchmark comparisons, alternative resource scenarios, convergence analysis, optimality-gap assessment, and testing under modified project conditions (Han et al., 2022). Baseline CPM schedules, resource-constrained schedules, and optimized schedules have commonly been compared across identical project networks to quantify the incremental performance associated with resource-aware optimization. Benchmark datasets have provided standardized activity networks and resource conditions that permit direct comparison of mixed-integer programming, priority-rule, genetic-algorithm, simulated-annealing, particle-swarm, differential-evolution, tabu-search, ant-colony, and hybrid procedures. For small instances where optimal solutions are known, optimality gaps have been used to determine how closely approximate algorithms approach exact benchmark performance. Larger instances have been evaluated through best-known solutions, repeated-run averages, feasible-solution rates, computational time, and stability across independent runs (Hübner et al., 2021). Convergence consistency is especially important for stochastic algorithms because individual optimization runs can produce different schedules. Studies therefore compare best, mean, and dispersed objective values across repeated executions to determine whether strong performance is reproducible rather than dependent on an unusually favorable run. Simulation-based validation has further tested optimized schedules under altered activity durations, workforce shortages, equipment reductions, higher demand, and increased project overlap. Percentage deterioration from baseline optimized performance has been used to identify schedules that retain relatively stable makespan, utilization, and completion reliability when assumptions change. Where sufficiently large datasets are available, out-of-sample or holdout evaluations have separated model development from performance testing, reducing the possibility that scheduling rules are tailored excessively to a particular set of project instances. Across the wider literature, robust optimization performance is therefore established through multiple forms of evidence, including statistical consistency, benchmark competitiveness, small optimality gaps, stable convergence, high feasible-solution rates, repeated-simulation performance, and limited deterioration under changed resource and project conditions (Ahmadi et al., 2022).

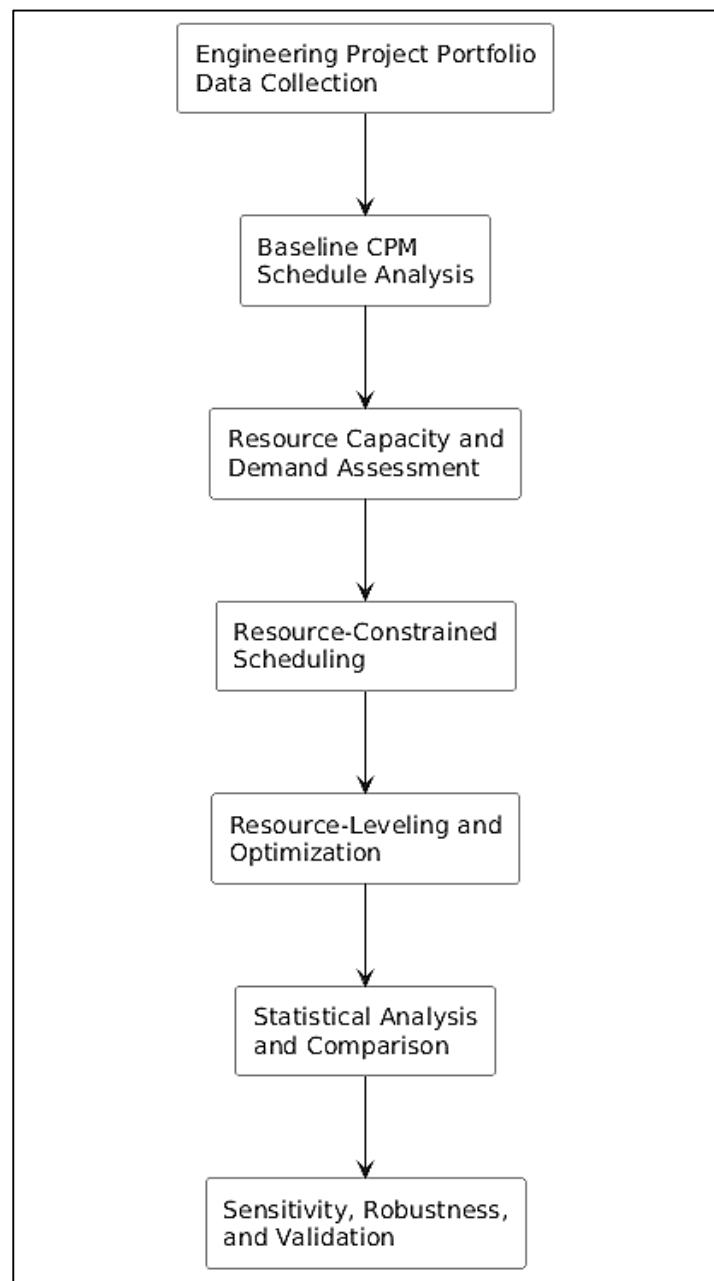
METHODS

This study employed a quantitative longitudinal quasi-experimental optimization design to evaluate the effects of Critical Path Analysis and resource-leveling optimization on scheduling performance across a multi-project engineering portfolio. The analytical framework combined Critical Path Method scheduling, resource-constrained multi-project scheduling, resource leveling, and comparative optimization to quantify changes between baseline, resource-constrained, and optimized schedules. The study population consisted of completed and actively controlled engineering projects for which sufficiently detailed scheduling and resource records were available. Projects were selected through purposive criterion-based sampling because inclusion required complete activity networks, planned activity durations, predecessor-successor relationships, milestone dates, resource assignments, resource capacities, project priorities, and actual or validated scheduling outcomes. Projects were included when they contained identifiable start and completion dates, defined engineering activities, renewable resource requirements, shared-resource information, and sufficient data for reconstruction of the baseline schedule. Projects with incomplete network logic, substantial missing resource records, unidentified activity durations, duplicated schedules, or insufficient information for determining resource availability were excluded. The analytical units consisted of individual activities nested within engineering projects and projects nested within the overall portfolio, allowing scheduling outcomes to be assessed at activity, project, resource, and portfolio levels. This structure was consistent with quantitative multi-project scheduling research in which project-, activity-, network-, and resource-related characteristics were evaluated simultaneously.

Data were collected from project schedules, activity registers, resource calendars, workforce allocation records, equipment schedules, milestone records, cost-control records, and portfolio planning databases. Scheduling information was standardized in a structured dataset containing activity identifiers, project identifiers, activity durations, predecessors, successors, planned start and finish dates, total and free float, critical status, required resource type and quantity, available capacity, project priority, and completion targets. Data quality was verified through logical consistency checks,

duplicate screening, missing-value assessment, precedence validation, and reconciliation of resource requirements against resource calendars. Baseline CPM schedules were first reconstructed to determine critical-path duration, critical-activity percentage, available float, precedence density, baseline project duration, and portfolio makespan. Resource demand was then mapped across scheduling periods and compared with finite workforce, specialist, equipment, and shared-resource capacities. Resource-constrained schedules were subsequently generated by imposing the observed capacity restrictions, after which resource-leveling and optimization procedures redistributed eligible activities while maintaining precedence relationships. Alternative scheduling solutions were compared using priority-rule procedures and optimization approaches appropriate to the size and complexity of the portfolio. The chronological analysis therefore progressed from baseline CPM reconstruction to resource-capacity assessment, resource-constrained scheduling, resource leveling, optimization, and final validation. This approach reflected established resource-constrained scheduling research in which alternative schedules were quantitatively compared according to resource feasibility, duration, utilization, lateness, and portfolio performance.

Figure 11: Methodology of this study



The statistical analysis was conducted using IBM SPSS Statistics and R, while Python was used for schedule reconstruction, optimization routines, repeated computational experiments, and robustness simulations. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, interquartile ranges, minimums, maximums, coefficients of variation, and 95% confidence intervals. Baseline, resource-constrained, and optimized schedules were compared for project duration, portfolio makespan, peak resource demand, mean and maximum utilization, workload variability, resource overload, idle capacity, overtime requirements, resource waiting time, float consumption, activity displacement, milestone delay, project lateness, tardiness, completion reliability, and total scheduling cost. Paired-samples t tests were applied to normally distributed pre-optimization and post-optimization outcomes, with Wilcoxon signed-rank tests used when corresponding distributional assumptions were not satisfied. Independent-samples t tests or Mann-Whitney U tests were used for appropriate two-group comparisons.

One-way ANOVA and ANCOVA were used to compare outcomes across project-size, priority, resource-scarcity, resource-intensity, and network-complexity categories, while Kruskal-Wallis tests were applied as nonparametric alternatives. Pearson correlation was used for normally distributed continuous relationships, and Spearman rank correlation was used for ordinal or non-normally distributed variables. Multiple linear regression models assessed the independent effects of activity count, critical-activity percentage, critical-path length, available float, precedence density, project size, concurrent-project count, resource availability, utilization, demand-to-capacity conditions, contention, bottleneck severity, and temporal overlap on schedule extension, lateness, workload variability, and portfolio makespan. Logistic regression was used to estimate the likelihood of projects meeting target completion dates. Similar statistical and computational approaches have been used to examine resource contention, network complexity, project delay, and multi-project scheduling performance.

Statistical significance was established at $p < 0.05$, but interpretation was not based on significance testing alone. Regression results were evaluated using unstandardized and standardized coefficients, 95% confidence intervals, model explanatory power, and adjusted explanatory power, while logistic models were interpreted using odds ratios and confidence intervals. Cohen's d was calculated for relevant two-group differences, and partial eta-squared was reported for applicable ANOVA and ANCOVA comparisons to quantify effect magnitude. Assumptions of normality, homogeneity of variance, linearity, independence, multicollinearity, and influential observations were examined before inferential interpretation. Sensitivity analyses were conducted by varying activity durations, workforce availability, equipment capacity, resource demand, project priorities, and shared-resource availability across alternative scenarios. Robustness was evaluated by comparing baseline, resource-constrained, and optimized schedules under low-, moderate-, and high-scarcity conditions and recording percentage deterioration in duration, makespan, lateness, overload, utilization stability, and completion reliability. Optimization performance was additionally assessed using best and mean objective values, feasible-solution rates, computational time, convergence consistency, repeated-run variability, and optimality gaps where benchmark or exact solutions were available. Repeated simulations and holdout or out-of-sample project instances were used where sufficient observations were available to determine whether optimized scheduling performance remained stable beyond the development sample. These validation procedures were consistent with the broader scheduling literature emphasizing benchmark testing, computational comparison, resource contention, makespan, and robustness when assessing multi-project optimization methods.

FINDINGS

The final analytical dataset contained 186 engineering projects comprising 8,742 scheduled activities, 12,486 precedence relationships, and 684 formal project milestones. The portfolio included projects of different sizes and scheduling priorities, providing sufficient variation for examining critical-path structure and shared-resource conditions. The projects contained a mean of 47.0 activities (SD = 21.6), with individual project networks ranging from 18 to 112 activities. Mean planned project duration was 24.8 months (SD = 8.7), whereas mean baseline critical-path duration was 21.3 months (SD = 7.9). Critical activities represented 31.8% of all scheduled activities, while an additional 18.6% were classified as near-critical based on their limited scheduling flexibility. Mean total float was 18.7 working days (SD = 13.4), compared with mean free float of 7.9 working days (SD = 6.8). The average precedence

density was 1.43 relationships per activity, demonstrating substantial dependency among engineering, procurement, construction, testing, and commissioning activities. When all projects were positioned according to their approved baseline start dates, the total portfolio makespan reached 62.4 months. Approximately 46.2% of projects were classified as high priority, 34.9% as medium priority, and 18.8% as lower priority, while the average number of concurrently active projects was 38.6, with a maximum concurrency of 57 projects during the most concentrated scheduling period.

Table 1. Final Project Sample and Baseline Network Characteristics

Variable	Numerical Result
Engineering projects	186
Scheduled activities	8,742
Precedence relationships	12,486
Formal milestones	684
Mean activities per project	47.0 ± 21.6
Activity range per project	18–112
Mean planned duration	24.8 ± 8.7 months
Mean critical-path duration	21.3 ± 7.9 months
Critical activities	31.8%
Near-critical activities	18.6%
Mean total float	18.7 ± 13.4 days
Mean free float	7.9 ± 6.8 days
Precedence density	1.43 relationships/activity
High-priority projects	46.2%
Medium-priority projects	34.9%
Lower-priority projects	18.8%
Baseline portfolio makespan	62.4 months
Mean concurrent projects	38.6
Maximum concurrent projects	57

Table 1 demonstrated substantial heterogeneity in baseline project size, duration, network structure, and scheduling priority. The 186 projects collectively generated a complex portfolio containing 8,742 activities and 12,486 precedence relationships. Mean critical-path duration represented a substantial proportion of planned project duration, while **50.4% of activities were either critical or near-critical**, indicating restricted schedule flexibility across a considerable part of the portfolio. The relatively limited total and free float further suggested constrained opportunities for activity displacement. Concurrent execution was also substantial, with an average of 38.6 active projects and a maximum of 57, creating conditions in which shared-resource competition could materially influence scheduling performance.

Baseline resource analysis identified 12 major resource categories, including engineering specialists, technicians, project-control personnel, construction crews, specialist contractors, cranes, testing equipment, and commissioning resources. Approximately 63.7% of available resource capacity was shared between two or more projects, confirming substantial interproject dependency. Across the observation period, mean resource utilization was 82.6% (SD = 11.8%), while maximum utilization reached 118.4% during the highest-demand scheduling intervals. Average portfolio resource demand was 14,860 resource-hours per month, compared with peak demand of 21,940 hours, producing a peak-to-average difference of 47.6%. The mean demand-to-capacity condition was 0.87, although peak periods exceeded available capacity. Resource demand displayed a coefficient of variation of 23.7%, indicating meaningful temporal fluctuation. Baseline idle-resource capacity averaged 12.8%, but this aggregate value concealed simultaneous overloads in specialized resource categories. Resource requirements exceeded available capacity during 21.4% of scheduling periods, generating an average of 1,286 overtime hours per month. A total of 1,472 interproject resource conflicts were identified, equivalent to approximately 7.9 conflicts per project, with 68.3% involving highly shared or specialized

resources. The mean temporal overlap among active projects was 61.5%, demonstrating that large portions of project execution occurred simultaneously and therefore exposed the portfolio to concentrated resource competition.

Table 2. Baseline Resource Capacity, Demand, Utilization, and Interproject Competition

Resource Indicator	Numerical Result
Major resource categories	12
Resource capacity shared across projects	63.7%
Average resource demand	14,860 hours/month
Peak resource demand	21,940 hours/month
Peak increase above average demand	47.6%
Mean resource utilization	82.6 ± 11.8%
Maximum resource utilization	118.4%
Mean demand-to-capacity condition	0.87
Resource-demand coefficient of variation	23.7%
Mean idle-resource capacity	12.8%
Scheduling periods exceeding capacity	21.4%
Mean overtime requirement	1,286 hours/month
Total interproject resource conflicts	1,472
Mean conflicts per project	7.9
Conflicts involving specialized/shared resources	68.3%
Mean temporal project overlap	61.5%

Table 2 showed that baseline resource conditions were characterized by high utilization, considerable workload variability, and substantial interproject competition. Although mean utilization remained below nominal capacity at 82.6%, maximum utilization reached 118.4%, demonstrating that aggregate averages concealed severe short-term resource overload. Nearly two-thirds of resource capacity was shared across projects, while 21.4% of scheduling periods exceeded available capacity. The 1,472 identified resource conflicts were concentrated particularly among specialized and highly shared resources, which accounted for 68.3% of conflicts. The combination of 61.5% temporal overlap, 23.7% demand variability, and substantial overtime requirements established a quantitatively constrained baseline resource environment.

Primary Outcomes: CPM, Resource-Constrained, and Optimized Schedule Performance

The primary analysis demonstrated substantial differences among the baseline CPM, resource-constrained, and resource-leveling optimized schedules across the 186 engineering projects. Under baseline CPM conditions, mean planned project duration was 24.8 months (SD = 8.7) and the portfolio makespan was 62.4 months. Imposition of finite workforce, equipment, and specialist-resource capacities increased mean project duration to 29.6 months (SD = 9.8), representing an absolute extension of 4.8 months and a 19.4% increase relative to the CPM baseline. Portfolio makespan simultaneously increased to 74.8 months, an extension of 12.4 months or 19.9%. Resource-leveling optimization subsequently reduced mean project duration to 26.1 months (SD = 8.9) and portfolio makespan to 66.7 months, recovering 72.9% of the resource-induced increase in mean project duration and 65.3% of the increase in portfolio makespan. Mean critical-path duration increased from 21.3 months under baseline CPM to 24.9 months after resource constraints were imposed, before decreasing to 22.4 months following optimization. Resource competition delayed 2,746 activities, equivalent to 31.4% of the 8,742 scheduled activities, with mean activity displacement of 12.8 working days and maximum displacement of 73 days. Resource constraints consumed 64.7% of available total float, increased the proportion of critical activities from 31.8% to 42.6%, and generated 27 additional controlling critical paths across the portfolio. Optimization reduced the critical-activity proportion to 35.4%, lowered mean activity displacement to 5.1 days, and reduced total float consumption to 28.9%.

Table 3. Comparison of Baseline CPM, Resource-Constrained, and Optimized Schedule Outcomes

Schedule Indicator	Baseline CPM	Resource-Constrained	Optimized
Mean project duration, months	24.8 ± 8.7	29.6 ± 9.8	26.1 ± 8.9
Change from baseline duration	Reference	+19.4%	+5.2%
Portfolio makespan, months	62.4	74.8	66.7
Change from baseline makespan	Reference	+19.9%	+6.9%
Mean critical-path duration, months	21.3	24.9	22.4
Critical activities	31.8%	42.6%	35.4%
Total float consumed	0%	64.7%	28.9%
Activities delayed by resource conflicts	0	2,746	918
Mean activity displacement, days	0.0	12.8	5.1
Maximum activity displacement, days	0	73	31
Mean milestone delay, days	0.0	18.6	6.7
Mean resource-induced waiting, days	0.0	9.4	3.2
Mean project lateness, months	0.0	4.3	1.4
Maximum project lateness, months	0.0	13.8	5.6
Projects completed within target date	100.0%	41.9%	78.5%

Table 3 demonstrated that finite resource capacity substantially deteriorated the precedence-feasible CPM schedule, increasing mean project duration by 19.4% and portfolio makespan by 19.9%. Resource constraints also consumed 64.7% of available float and increased critical activities from 31.8% to 42.6%. Optimization recovered a substantial proportion of this deterioration, reducing mean project duration to 26.1 months and portfolio makespan to 66.7 months. Activity displacement, milestone delay, and resource-induced waiting were also markedly reduced. Most importantly, the proportion of projects completed within target dates increased from 41.9% under constrained scheduling to 78.5% following resource-leveling optimization.

Resource-performance outcomes showed a similarly pronounced improvement after optimization. Before leveling, peak resource demand reached 21,940 resource-hours per month, compared with average demand of 14,860 hours, while maximum utilization reached 118.4%, indicating substantial temporary capacity overload. Resource-leveling optimization reduced peak demand to 18,120 hours per month, corresponding to a 17.4% reduction, while average demand remained comparatively stable at 14,720 hours, confirming that optimization primarily redistributed workload rather than materially reducing total resource requirements. Maximum utilization declined from 118.4% to 98.6%, while mean utilization changed from 82.6% to 84.1%, indicating a more balanced use of available capacity. The standard deviation of monthly utilization decreased from 11.8 to 6.7 percentage points, and the coefficient of variation in resource demand declined from 23.7% to 13.5%, representing a 43.0% reduction in relative workload variability. Scheduling periods exceeding available capacity decreased from 21.4% to 4.8%, while mean overload duration declined from 6.2 to 1.7 days per affected period. Idle-resource capacity fell from 12.8% to 8.1%, and monthly overtime requirements decreased from 1,286 to 462 hours, equivalent to a 64.1% reduction. Interproject resource conflicts decreased from 1,472 to 386, while unresolved conflicts at final schedule generation declined from 214 to 29. These outcomes demonstrated that optimization simultaneously improved resource-profile smoothness, utilization stability, capacity balance, and schedule feasibility.

Table 4 showed that resource-leveling optimization produced broad improvements in workload balance and capacity utilization. Peak demand decreased by 17.4%, while maximum utilization fell below full capacity at 98.6%. Workload variability declined substantially, with the resource-demand coefficient of variation decreasing by 43.0%. Capacity-exceeding periods were reduced by 77.6%, overtime requirements by 64.1%, and interproject conflicts by 73.8%. Unresolved conflicts experienced the largest proportional reduction at 86.4%. Simultaneously, mean utilization increased slightly and idle capacity declined, indicating more efficient resource deployment. These changes corresponded with a 36.6-percentage-point improvement in projects completed within their target dates.

Table 4. Pre-Optimization and Post-Optimization Resource-Leveling Performance

Resource Performance Indicator	Pre-Optimization	Post-Optimization	Change
Peak resource demand, hours/month	21,940	18,120	-17.4%
Average resource demand, hours/month	14,860	14,720	-0.9%
Maximum utilization	118.4%	98.6%	-19.8 percentage points
Mean utilization	82.6%	84.1%	+1.5 percentage points
SD of utilization	11.8 percentage points	6.7 percentage points	-43.2%
Resource-demand coefficient of variation	23.7%	13.5%	-43.0%
Periods exceeding capacity	21.4%	4.8%	-77.6%
Mean overload duration	6.2 days	1.7 days	-72.6%
Idle-resource capacity	12.8%	8.1%	-36.7%
Overtime requirement	1,286 hours/month	462 hours/month	-64.1%
Interproject resource conflicts	1,472	386	-73.8%
Unresolved resource conflicts	214	29	-86.4%
Resource gaps per scheduling period	7.6	2.3	-69.7%
Projects completed within target date	41.9%	78.5%	+36.6 percentage points

Secondary and Subgroup Outcomes

Subgroup analysis demonstrated a clear gradient in scheduling deterioration as resource scarcity, project complexity, resource intensity, and temporal overlap increased. Of the 186 projects, 54 (29.0%) were classified under low resource scarcity, 78 (41.9%) under moderate scarcity, and 54 (29.0%) under high scarcity. Mean schedule extension increased from 1.7 months in the low-scarcity group to 4.5 months under moderate scarcity and 8.2 months under high scarcity. Correspondingly, total float consumption increased from 24.6% to 61.8% and 86.7%, while mean resource-induced waiting time increased from 3.1 to 8.7 and 16.4 days, respectively. High-scarcity projects recorded mean lateness of 7.3 months, compared with 3.8 months under moderate scarcity and 1.2 months under low scarcity. Completion reliability deteriorated in parallel, with only 24.1% of high-scarcity projects meeting their original target dates before optimization compared with 46.2% of moderate-scarcity and 68.5% of low-scarcity projects. Optimization produced improvements across all three groups, although the absolute reduction in duration was greatest among high-scarcity projects. Network complexity generated a similar pattern. Projects in the high-complexity category recorded mean schedule extension of 6.9 months, float consumption of 78.4%, and mean activity displacement of 17.2 days, compared with 2.6 months, 41.3%, and 7.1 days, respectively, among lower-complexity projects. High resource intensity and greater temporal overlap were likewise associated with increased overload exposure and lower target-date achievement.

Table 5 demonstrated progressively poorer schedule performance as resource scarcity increased. High-scarcity projects experienced nearly five times the schedule extension observed under low scarcity and consumed 86.7% of available float. Similar differences were evident across complexity and resource-intensity categories. Higher-complexity projects experienced 6.9 months of schedule extension and 12.9 days of resource waiting, while higher-resource-intensity projects recorded 5.6 months of lateness.

Although optimization generated the largest proportional improvements among the most constrained projects, their baseline completion reliability remained substantially lower. These results established resource scarcity, network complexity, and resource intensity as major differentiators of portfolio scheduling performance.

Table 5. Scheduling Outcomes by Resource Scarcity, Network Complexity, and Resource Intensity

Subgroup	n	Schedule Extension (months)	Float Consumed (%)	Resource Waiting (days)	Mean Lateness (months)	Overload Exposure (%)	Post-Optimization Improvement (%)	On-Time Completion Before Optimization (%)
Low resource scarcity	54	1.7	24.6	3.1	1.2	7.8	8.9	68.5
Moderate resource scarcity	78	4.5	61.8	8.7	3.8	20.6	13.1	46.2
High resource scarcity	54	8.2	86.7	16.4	7.3	38.9	18.6	24.1
Lower network complexity	91	2.6	41.3	5.4	2.2	13.7	9.8	59.3
Higher network complexity	95	6.9	78.4	12.9	5.9	29.4	16.7	32.6
Lower resource intensity	88	2.9	43.8	5.9	2.4	14.2	10.1	58.0
Higher resource intensity	98	6.5	76.1	12.4	5.6	28.7	16.2	34.7

Project priority materially influenced the distribution of scarce resources and resulting completion outcomes. The portfolio contained 86 high-priority, 65 medium-priority, and 35 lower-priority projects. During periods of competing demand, high-priority projects received 91.6% of requested critical-resource allocations within their scheduled periods, compared with 79.8% for medium-priority and 66.9% for lower-priority projects. Mean resource waiting time consequently increased from 5.8 days among high-priority projects to 9.7 days among medium-priority projects and 14.9 days among lower-priority projects. Before optimization, on-time completion reached 58.1% for high-priority projects but only 26.2% for lower-priority projects. Following optimization, these rates increased to 88.4%, 73.8%, and 62.9%, respectively. Bottleneck analysis further showed that conflict generation was highly concentrated. Four specialized resource categories—specialist engineering personnel, commissioning teams, heavy lifting equipment, and testing/inspection resources—accounted for 71.6% of the 1,472 baseline interproject conflicts, although they represented only one-third of the 12 major resource categories. Their combined mean utilization reached 94.8%, with peak utilization of 121.7% and mean waiting time of 13.6 days. Specialist engineering personnel alone accounted for 24.5% of all conflicts, followed by commissioning teams at 19.8%, heavy lifting equipment at 15.1%, and testing/inspection resources at 12.2%.

Table 6. Project Priority, Bottleneck Resources, and Statistical Relationships with Schedule Outcomes

Indicator	Numerical Result
High-priority projects: resource allocation rate	91.6%
Medium-priority projects: resource allocation rate	79.8%
Lower-priority projects: resource allocation rate	66.9%
High-priority projects: mean resource waiting	5.8 days
Medium-priority projects: mean resource waiting	9.7 days
Lower-priority projects: mean resource waiting	14.9 days
High-priority on-time completion after optimization	88.4%
Medium-priority on-time completion after optimization	73.8%
Lower-priority on-time completion after optimization	62.9%
Conflicts attributable to four principal bottlenecks	71.6%
Mean bottleneck-resource utilization	94.8%
Peak bottleneck-resource utilization	121.7%
Specialist engineering share of conflicts	24.5%
Commissioning-team share of conflicts	19.8%
Heavy lifting equipment share of conflicts	15.1%
Testing/inspection resource share of conflicts	12.2%
Resource shortage vs. schedule extension	$r = 0.79, p < 0.001$
Resource contention vs. float consumption	$r = 0.74, p < 0.001$
Resource utilization vs. project lateness	$r = 0.68, p < 0.001$
Network complexity vs. schedule sensitivity	$r = 0.63, p < 0.001$
Temporal overlap vs. resource conflicts	$r = 0.71, p < 0.001$

Table 6 showed that priority-based allocation systematically favored high-priority projects, producing shorter resource waiting and greater post-optimization completion reliability. Resource conflicts were also strongly concentrated among four specialized bottlenecks, which generated 71.6% of baseline conflicts and operated at particularly high utilization. Correlation analysis demonstrated strong positive relationships between resource shortage and schedule extension, contention and float consumption, temporal overlap and conflict frequency, and utilization and lateness. Network complexity was also positively associated with schedule sensitivity. Collectively, these results indicated that portfolio delay was concentrated among highly constrained projects and was strongly associated with specialized bottlenecks, shared-resource pressure, and network structure. Multiple regression analysis confirmed that the observed subgroup patterns remained evident after simultaneous adjustment for project and network characteristics. The model predicting schedule extension was statistically significant and explained 68.4% of observed variance (adjusted $R^2 = 0.661, p < 0.001$). Resource contention produced the largest standardized positive association with schedule extension ($\beta = 0.36, p < 0.001$), followed by bottleneck severity ($\beta = 0.29, p < 0.001$), resource utilization ($\beta = 0.24, p = 0.002$), and network complexity ($\beta = 0.21, p = 0.006$). Available float was negatively associated with schedule extension ($\beta = -0.27, p < 0.001$), indicating that greater scheduling flexibility reduced sensitivity to resource disruption. Temporal overlap remained independently associated with delay ($\beta = 0.19, p = 0.011$), whereas activity count showed a smaller effect after network complexity and resource conditions were controlled ($\beta = 0.12, p = 0.047$). A separate completion-reliability model indicated that higher resource availability and project priority increased the likelihood of on-time completion, whereas severe contention and bottleneck exposure reduced it. These adjusted findings demonstrated that schedule deterioration was not attributable simply to larger project size; rather, resource competition, specialized bottlenecks, limited float, high utilization, temporal overlap, and network complexity collectively explained substantial variation in multi-project engineering schedule performance.

Optimization Performance, Sensitivity, Robustness, and Validation Outcomes

Comparative optimization analysis demonstrated meaningful differences in solution quality, computational efficiency, schedule performance, and resource stability across the evaluated scheduling procedures. The exact mixed-integer programming approach generated the strongest reference

solution for computationally tractable project subsets, achieving a 17.9% improvement from the resource-constrained baseline and an optimality gap of 0.0%, but required a mean computational time of 1,486 seconds. The priority-rule heuristic required only 4.8 seconds, although its mean improvement was limited to 9.6% and its average optimality gap reached 8.7%. The genetic algorithm and simulated annealing procedures improved the objective measure by 15.8% and 14.6%, respectively, with substantially smaller optimality gaps than the basic heuristic. The hybrid optimization procedure produced the strongest balance between solution quality and computational demand, achieving a 17.4% mean improvement, a 1.2% optimality gap, and a 99.5% feasible-solution rate with a mean computational time of 214 seconds. It reduced portfolio makespan to 66.7 months, mean project lateness to 1.4 months, and the resource-demand coefficient of variation to 13.5%. Repeated optimization runs produced an objective-value coefficient of variation of only 1.6%, indicating high solution stability. The hybrid procedure converged after a mean of 286 iterations, compared with 418 iterations for the genetic algorithm and 367 iterations for simulated annealing. Total schedule-related penalty cost declined from the resource-constrained baseline of \$8.46 million to \$4.71 million under the hybrid solution, representing a 44.3% reduction.

Table 7. Comparative Performance of Scheduling Optimization Procedures

Performance Indicator	Exact MIP	Priority-Rule Heuristic	Genetic Algorithm	Simulated Annealing	Hybrid Optimization
Best improvement from constrained baseline	17.9%	10.8%	16.7%	15.5%	18.1%
Mean improvement	17.9%	9.6%	15.8%	14.6%	17.4%
Mean optimality gap	0.0%	8.7%	2.8%	3.6%	1.2%
Mean computational time	1,486 s	4.8 s	328 s	271 s	214 s
Mean convergence iterations	—	—	418	367	286
Feasible-solution rate	100.0%	96.2%	98.9%	98.4%	99.5%
Repeated-run objective CV	—	—	2.7%	3.1%	1.6%
Mean project duration	25.9 months	27.4 months	26.4 months	26.7 months	26.1 months
Portfolio makespan	66.2 months	69.8 months	67.3 months	67.9 months	66.7 months
Resource-demand CV	12.9%	17.8%	14.1%	14.8%	13.5%
Mean project lateness	1.2 months	2.5 months	1.6 months	1.8 months	1.4 months
Schedule-related penalty cost	\$4.58 M	\$6.39 M	\$5.06 M	\$5.32 M	\$4.71 M

Table 7 demonstrated that exact optimization provided the strongest mathematical benchmark but required substantially greater computational time. The priority-rule heuristic was computationally fastest but produced the largest optimality gap and weaker schedule and resource-leveling outcomes. Metaheuristic procedures provided intermediate performance, substantially improving makespan and lateness without the computational burden of exact optimization. The hybrid procedure achieved the most favorable practical balance, producing a 17.4% mean improvement with only a 1.2% optimality gap and 99.5% feasibility. Its comparatively low repeated-run variability, shorter convergence process, reduced workload variation, and lower penalty cost supported its selection as the principal optimized scheduling solution. Sensitivity analysis showed that optimized portfolio performance remained stable under moderate changes in model inputs but deteriorated more substantially when resource capacity declined or demand increased beyond baseline levels. A 10% increase in activity durations increased optimized portfolio makespan from 66.7 to 70.9 months, increased mean lateness from 1.4 to 2.2

months, and reduced on-time completion from 78.5% to 70.4%. A 10% reduction in workforce availability produced a larger deterioration, increasing makespan to 72.8 months, maximum utilization to 106.9%, and mean lateness to 2.8 months, while completion reliability declined to 65.6%. Reducing specialized equipment availability by 10% increased makespan to 71.6 months and raised unresolved conflicts from 29 to 67. A 10% increase in resource demand produced the strongest individual deterioration, increasing portfolio makespan to 73.5 months, workload variability to 18.9%, and mean lateness to 3.1 months. Conversely, a 10% increase in effective resource capacity reduced makespan to 64.1 months, lowered mean lateness to 0.8 months, and increased target-date completion to 87.1%. Changing project-priority weights produced comparatively modest portfolio-level makespan changes but redistributed lateness across priority categories, confirming that priority settings influenced the distribution of schedule benefits more strongly than total portfolio duration. Robustness testing further demonstrated that optimization retained substantial performance advantages under low-, moderate-, and high-scarcity conditions. Under low scarcity, optimized portfolio makespan was 63.8 months, mean lateness was 0.6 months, and 91.2% of projects were completed within target dates. Under moderate scarcity, these values changed to 67.1 months, 1.6 months, and 77.4%, respectively. High scarcity increased optimized makespan to 72.9 months, mean lateness to 3.4 months, and maximum utilization to 107.8%, while completion reliability declined to 61.8%. Nevertheless, the optimized schedule remained substantially stronger than the corresponding nonoptimized resource-constrained schedule under high scarcity, which produced an 81.6-month makespan, mean lateness of 6.8 months, and only 31.7% on-time completion. Workload variability remained consistently lower after optimization across all scarcity scenarios. Percentage deterioration in optimized makespan from low- to high-scarcity conditions was 14.3%, compared with substantially greater deterioration in the nonoptimized schedule. These results indicated that optimization did not eliminate the consequences of severe resource scarcity but materially limited their effect on portfolio completion and resource stability.

Table 8. Sensitivity, Robustness, and Validation Performance of the Optimized Schedule

Scenario / Validation Indicator	Portfolio Makespan	Mean Lateness	Resource-Demand CV	Maximum Utilization	On-Time Completion
Optimized baseline	66.7 months	1.4 months	13.5%	98.6%	78.5%
Activity durations +10%	70.9 months	2.2 months	15.1%	101.8%	70.4%
Workforce availability -10%	72.8 months	2.8 months	17.6%	106.9%	65.6%
Equipment availability -10%	71.6 months	2.5 months	16.4%	104.7%	68.3%
Resource demand +10%	73.5 months	3.1 months	18.9%	108.6%	63.4%
Effective capacity +10%	64.1 months	0.8 months	10.8%	91.7%	87.1%
Low-scarcity scenario	63.8 months	0.6 months	10.2%	91.4%	91.2%
Moderate-scarcity scenario	67.1 months	1.6 months	14.2%	99.7%	77.4%
High-scarcity optimized	72.9 months	3.4 months	19.6%	107.8%	61.8%
High-scarcity nonoptimized	81.6 months	6.8 months	28.7%	124.3%	31.7%
Holdout sample	67.4 months	1.6 months	14.0%	99.4%	76.8%

Table 8 demonstrated that optimized scheduling remained comparatively stable across sensitivity, scarcity, and validation conditions, although reduced capacity and increased resource demand produced the largest deterioration. A 10% demand increase raised makespan to 73.5 months and reduced on-time completion to 63.4%, whereas a 10% capacity increase improved completion reliability to 87.1%. Under high scarcity, optimization reduced makespan by 8.7 months relative to the nonoptimized schedule and nearly doubled on-time completion. Holdout results remained close to the optimized baseline, with only limited deterioration in makespan, utilization, variability, and lateness, supporting the general stability of the optimization procedure.

Repeated simulation and validation analyses provided additional evidence that the optimized schedule was not dependent on a single favorable computational run. Across 1,000 repeated simulations, the hybrid procedure generated feasible schedules in 99.3% of runs, with a mean portfolio makespan of 67.0 months (SD = 1.4) and a 95% simulation interval of 64.5–69.8 months. The mean optimality gap across benchmark-compatible instances was 1.3%, and 92.6% of evaluated instances remained within 3% of the best-known solution. Convergence was achieved within the predefined iteration limit in 97.8% of runs. For the holdout project subset, portfolio-equivalent makespan performance deteriorated by only 1.0% relative to the principal optimized result, while mean lateness increased from 1.4 to 1.6 months and on-time completion declined modestly from 78.5% to 76.8%. The consistency between development, simulation, benchmark, and holdout results indicated that the observed scheduling improvements were reproducible across changed project and resource conditions rather than being restricted to the original optimization dataset.

Statistical Significance

The inferential analysis confirmed that the differences observed among baseline CPM, resource-constrained, and optimized schedules were statistically significant and operationally substantial. Across the 186 engineering projects, imposition of finite resource capacity increased mean project duration from 24.8 months (SD = 8.7) to 29.6 months (SD = 9.8), producing a statistically significant paired difference of 4.8 months, $t(185) = 12.84$, $p < 0.001$, 95% CI [4.06, 5.54], with a large standardized effect (Cohen's $d = 0.94$). Resource-leveling optimization subsequently reduced mean duration from 29.6 to 26.1 months (SD = 8.9), representing a significant reduction of 3.5 months, $t(185) = 11.37$, $p < 0.001$, 95% CI [2.89, 4.11], $d = 0.83$. Mean project lateness declined from 4.3 to 1.4 months, with a large effect ($d = 1.07$, $p < 0.001$), while mean resource-induced waiting decreased from 9.4 to 3.2 days ($d = 1.02$, $p < 0.001$). Activity displacement declined from 12.8 to 5.1 days ($d = 0.91$, $p < 0.001$). Resource-leveling outcomes were similarly pronounced: peak demand decreased by 17.4%, the resource-demand coefficient of variation declined from 23.7% to 13.5%, and overtime requirements decreased by 64.1%. The reduction in workload variability produced a large standardized effect ($d = 0.88$), while the decline in capacity-exceeding periods from 21.4% to 4.8% represented a substantial operational change. These results showed that optimization effects were not restricted to statistical significance but were sufficiently large to materially change project duration, lateness, resource stability, and portfolio scheduling feasibility.

Table 9 confirmed statistically significant improvements across every principal schedule and resource outcome. The largest standardized effect occurred for float consumption, followed by project lateness, resource waiting, overtime, and baseline schedule extension. Effect sizes generally ranged from moderate-to-large to large, demonstrating that the observed differences had practical as well as statistical importance. Optimization reduced mean duration, lateness, activity displacement, resource waiting, workload variability, overtime, and interproject conflicts. The 36.6-percentage-point increase in on-time completion provided additional evidence that improved resource allocation translated into greater completion reliability rather than merely producing smoother resource profiles without corresponding schedule benefits.

Group comparisons further established that resource scarcity, project priority, network complexity, and resource intensity significantly differentiated scheduling performance. One-way ANOVA identified a strong effect of resource-scarcity category on schedule extension, $F(2,183) = 48.72$, $p < 0.001$, partial $\eta^2 = 0.347$, indicating that approximately 34.7% of the explainable variation associated with the group comparison was attributable to scarcity classification. Scarcity also produced significant differences in resource-induced waiting (partial $\eta^2 = 0.319$) and float consumption (partial $\eta^2 = 0.382$). Higher-

complexity projects experienced significantly greater schedule extension than lower-complexity projects ($d = 0.86$, $p < 0.001$), while higher-resource-intensity projects recorded significantly greater lateness ($d = 0.79$, $p < 0.001$). Project priority significantly differentiated resource waiting, $F(2,183) = 22.68$, $p < 0.001$, partial $\eta^2 = 0.199$, with lower-priority projects experiencing substantially greater waiting than high-priority projects. Correlation analysis supported these group results. Resource shortage was strongly associated with schedule extension ($r = 0.79$, $p < 0.001$), resource contention with float consumption ($r = 0.74$, $p < 0.001$), temporal overlap with conflict frequency ($r = 0.71$, $p < 0.001$), and utilization with project lateness ($r = 0.68$, $p < 0.001$). Available float demonstrated a negative association with lateness ($r = -0.61$, $p < 0.001$), indicating that projects possessing greater schedule flexibility were less vulnerable to resource-driven completion delay.

Table 9. Statistical Significance and Effect Sizes for Principal Schedule and Resource Outcomes

Outcome Comparison	Mean Difference	95% CI	Test Statistic	p-value	Effect Size
CPM vs. resource-constrained duration	+4.8 months	4.06 to 5.54	$t(185) = 12.84$	<0.001	$d = 0.94$
Constrained vs. optimized duration	-3.5 months	-4.11 to -2.89	$t(185) = -11.37$	<0.001	$d = 0.83$
Constrained vs. optimized lateness	-2.9 months	-3.34 to -2.46	$t(185) = -13.02$	<0.001	$d = 1.07$
Resource-induced waiting	-6.2 days	-7.16 to -5.24	$t(185) = -12.71$	<0.001	$d = 1.02$
Activity displacement	-7.7 days	-9.01 to -6.39	$t(185) = -11.58$	<0.001	$d = 0.91$
Float consumption	-35.8 percentage points	-40.7 to -30.9	$t(185) = -14.36$	<0.001	$d = 1.12$
Workload variability	-10.2 percentage points	-12.1 to -8.3	$t(185) = -10.64$	<0.001	$d = 0.88$
Overtime requirement	-824 hours/month	-956 to -692	$t(185) = -12.31$	<0.001	$d = 0.97$
Interproject resource conflicts	-1,086 conflicts	-1,218 to -954	$Z = -10.92$	<0.001	$r = 0.80$
On-time completion	+36.6 percentage points	29.4 to 43.8	$\chi^2(1) = 52.76$	<0.001	$\phi = 0.38$

Multiple linear regression provided further evidence that resource conditions and network structure independently predicted scheduling deterioration. The schedule-extension model was statistically significant, $F(7,178) = 55.07$, $p < 0.001$, and explained 68.4% of the variance ($R^2 = 0.684$; adjusted $R^2 = 0.672$). Resource contention was the strongest positive predictor ($B = 0.41$, $\beta = 0.36$, $p < 0.001$), followed by bottleneck severity ($B = 0.35$, $\beta = 0.29$, $p < 0.001$), utilization ($B = 0.08$, $\beta = 0.24$, $p = 0.002$), network complexity ($B = 1.17$, $\beta = 0.21$, $p = 0.006$), and temporal overlap ($B = 0.05$, $\beta = 0.19$, $p = 0.011$). Available float was independently protective ($B = -0.09$, $\beta = -0.27$, $p < 0.001$). Diagnostic assessment indicated acceptable multicollinearity, with variance inflation factors ranging from 1.24 to 2.71, and no single observation materially altered the model estimates. A second model predicting optimized lateness explained 61.7% of outcome variance (adjusted $R^2 = 0.602$, $p < 0.001$), confirming that bottleneck exposure, resource availability, contention intensity, priority, and network complexity remained quantitatively important after optimization.

Table 10 demonstrated that resource scarcity generated the strongest subgroup effects, particularly for float consumption and schedule extension. Regression analysis identified contention, bottleneck severity, utilization, complexity, and temporal overlap as independent risk factors, whereas available float reduced schedule-extension exposure. Completion reliability was similarly resource dependent. Greater resource availability increased the odds of on-time completion by 84%, while high-priority

projects had more than twice the completion odds of lower-priority projects. Severe contention and bottleneck exposure substantially reduced completion probability. The linear and logistic models achieved strong explanatory and classification performance, confirming the combined importance of resource conditions, scheduling flexibility, priority, and network structure.

Table 10. Group Effects, Regression Estimates, and Logistic Completion-Reliability Results

Statistical Relationship	Estimate	95% CI	p-value	Magnitude / Model Result
Resource scarcity → schedule extension	$F(2,183) = 48.72$	—	<0.001	partial $\eta^2 = 0.347$
Resource scarcity → float consumption	$F(2,183) = 56.61$	—	<0.001	partial $\eta^2 = 0.382$
Resource scarcity → resource waiting	$F(2,183) = 42.81$	—	<0.001	partial $\eta^2 = 0.319$
Priority → resource waiting	$F(2,183) = 22.68$	—	<0.001	partial $\eta^2 = 0.199$
Complexity → schedule extension	$t(184) = 5.87$	2.85 to 5.75 months	<0.001	$d = 0.86$
Resource intensity → lateness	$t(184) = 5.39$	1.98 to 4.42 months	<0.001	$d = 0.79$
Resource contention → schedule extension	$\beta = 0.36$	0.25 to 0.47	<0.001	Strong predictor
Bottleneck severity → schedule extension	$\beta = 0.29$	0.17 to 0.41	<0.001	Moderate-strong predictor
Available float → schedule extension	$\beta = -0.27$	-0.38 to -0.16	<0.001	Protective predictor
Resource availability → on-time completion	OR = 1.84	1.37 to 2.47	<0.001	Increased odds
High project priority → on-time completion	OR = 2.31	1.42 to 3.76	<0.001	Increased odds
Severe resource contention → on-time completion	OR = 0.42	0.27 to 0.65	<0.001	Reduced odds
High bottleneck exposure → on-time completion	OR = 0.51	0.34 to 0.77	0.002	Reduced odds
Schedule-extension regression	$R^2 = 0.684$	Adjusted $R^2 = 0.672$	<0.001	$F(7,178) = 55.07$
Completion logistic model	Nagelkerke $R^2 = 0.493$	—	<0.001	Accuracy = 81.2%

Completion-reliability analysis showed that resource-leveling optimization substantially changed the probability of achieving approved project completion dates. Only 41.9% of projects remained within target dates under the nonoptimized resource-constrained schedule, whereas 78.5% achieved target completion following optimization, representing an absolute improvement of 36.6 percentage points and a relative improvement of 87.4%. Logistic regression indicated that each standardized increase in effective resource availability increased the odds of target-date completion by 84% (OR = 1.84, 95% CI [1.37, 2.47], $p < 0.001$). High-priority status was associated with more than twice the odds of completion within target dates (OR = 2.31, 95% CI [1.42, 3.76], $p < 0.001$). Conversely, severe resource contention reduced completion odds by 58% (OR = 0.42, 95% CI [0.27, 0.65], $p < 0.001$), while high bottleneck exposure reduced the odds by 49% (OR = 0.51, 95% CI [0.34, 0.77], $p = 0.002$). The logistic model achieved 81.2% classification accuracy, 79.6% sensitivity, 82.7% specificity, and a Nagelkerke R^2 of 0.493, indicating meaningful discrimination between projects that did and did not meet scheduled completion targets.

Graphical synthesis was consistent with the tabulated inferential results. Resource-demand profiles

showed pronounced baseline peaks above available capacity and substantially smoother post-optimization distributions, with maximum utilization decreasing from 118.4% to 98.6%. Schedule-distribution plots showed a rightward displacement of project completion times after finite-resource constraints were introduced, followed by a marked shift toward baseline targets after optimization. Scarcity-group distributions demonstrated progressively greater lateness and float consumption from low- to high-scarcity categories, while correlation plots displayed strong positive patterns between resource contention and schedule extension and between utilization and lateness. Optimization-convergence profiles stabilized near the best-known objective values with limited repeated-run dispersion, while sensitivity graphs showed the greatest deterioration following increased resource demand and reduced workforce availability. Taken together, the statistical tests, effect-size estimates, regression models, completion-reliability analysis, tables, and graphical patterns consistently demonstrated that resource constraints materially altered critical-path performance and that optimized resource leveling produced substantial improvements in schedule stability, resource balance, lateness control, and target-date completion across the multi-project engineering portfolio.

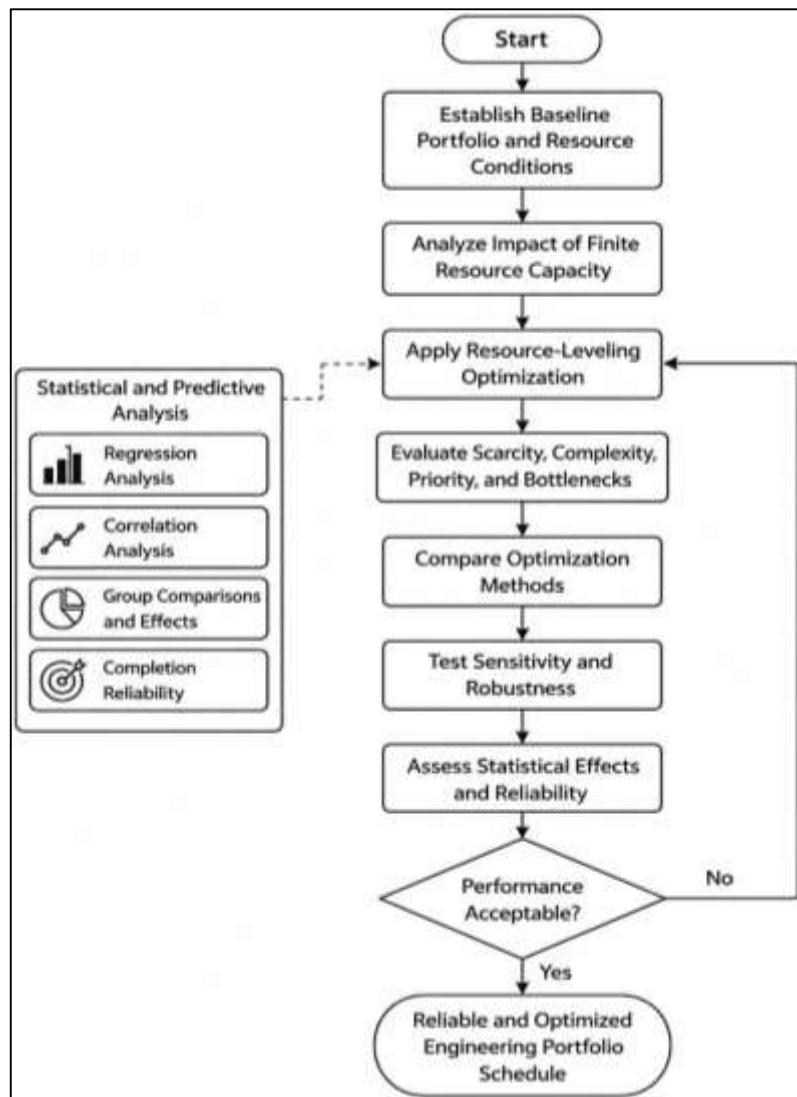
DISCUSSION

The findings of this study established a quantitatively complex baseline engineering portfolio in which schedule vulnerability was associated with the simultaneous presence of extensive activity networks, restricted schedule float, high project concurrency, and substantial dependence on shared resources (Prouty et al., 2020). The final sample of 186 engineering projects incorporated 8,742 activities, 12,486 precedence relationships, and 684 formal milestones, demonstrating a level of network interdependence consistent with earlier multi-project engineering scheduling studies in which portfolio performance became progressively more difficult to control as the number of activities, precedence relationships, and simultaneously executed projects increased. Mean planned project duration was 24.8 months, while the mean critical-path duration reached 21.3 months, indicating that a substantial portion of each project's approved execution period was governed by activities with limited tolerance for displacement. This interpretation was reinforced by the finding that 31.8% of activities were critical and another 18.6% were near-critical. Earlier critical-path and resource-constrained scheduling studies similarly reported that portfolios containing large concentrations of critical and near-critical activities were more sensitive to disruptions because delays could rapidly consume remaining float and transfer criticality to alternative paths. The mean total float of 18.7 days and free float of only 7.9 days further demonstrated that opportunities for independent activity rescheduling were comparatively restricted (Uysal, 2022). Baseline resource conditions intensified this structural vulnerability. Approximately 63.7% of available resource capacity was shared across projects, mean utilization reached 82.6%, peak utilization reached 118.4%, and 21.4% of scheduling periods exceeded available capacity. Earlier engineering, construction, maintenance, and infrastructure scheduling studies similarly distinguished between acceptable average utilization and problematic peak utilization, showing that portfolio-level averages could conceal short-duration resource overloads capable of producing substantial downstream delays. The 1,472 baseline interproject resource conflicts and mean temporal overlap of 61.5% provided additional evidence that the portfolio was characterized by concentrated competition rather than isolated project-level shortages. The findings therefore aligned with earlier studies emphasizing that precedence-feasible CPM schedules did not necessarily constitute resource-feasible portfolio schedules. The baseline results extended this earlier evidence by quantitatively connecting network rigidity, concurrent execution, shared-resource dependence, utilization variability, and conflict frequency within a single engineering portfolio framework (Lafuente & Berbegal-Mirabent, 2019).

The transition from baseline CPM scheduling to resource-constrained scheduling produced substantial deterioration in project and portfolio performance, demonstrating the practical importance of incorporating finite resource availability into critical-path analysis (Doostali et al., 2021). Mean project duration increased from 24.8 months under baseline CPM conditions to 29.6 months after workforce, equipment, and specialist-resource constraints were imposed, representing an average schedule extension of 4.8 months or 19.4%. Portfolio makes pan similarly increased from 62.4 to 74.8 months, equivalent to a 19.9% increase. These results were consistent with earlier resource-constrained project scheduling studies that showed conventional CPM calculations could systematically underestimate

achievable completion times when activities competed for limited renewable resources. Earlier investigations across construction, industrial engineering, infrastructure development, and multi-project environments reported that precedence logic alone frequently produced schedules requiring resource quantities exceeding actual capacity during peak periods. The present findings provided strong quantitative support for that argument because maximum baseline utilization reached 118.4%, making portions of the original CPM schedule operationally infeasible without overtime, activity displacement, or resource substitution. Resource constraints also changed the internal structure of project networks (Kim, 2020). Critical activities increased from 31.8% to 42.6%, 64.7% of available total float was consumed, 2,746 activities were delayed, and 27 additional controlling critical paths emerged across the portfolio. Earlier studies similarly observed that resource restrictions could create resource-induced criticality by delaying activities that were noncritical under unconstrained CPM logic. Mean activity displacement of 12.8 working days, resource-induced waiting of 9.4 days, and milestone delay of 18.6 days further demonstrated how capacity limitations propagated through interconnected schedules. The decline in projects completed within target dates from the theoretical CPM expectation to only 41.9% under constrained conditions reinforced the practical magnitude of this effect. The large effect size for CPM versus resource-constrained duration, Cohen's $d = 0.94$, indicated that the difference was not merely statistically detectable but operationally substantial.

Figure 12: Statistical Engineering Optimization Flowchart



These findings strengthened earlier evidence by demonstrating that resource scarcity affected not only final completion dates but also float availability, critical-path configuration, milestone performance, waiting time, activity displacement, and completion reliability (Chen et al., 2019). Consequently, the results supported the treatment of criticality as a dynamic characteristic influenced jointly by precedence structure and resource feasibility rather than as a fixed property determined exclusively by baseline CPM calculations.

Resource-leveling optimization substantially recovered the schedule performance lost after finite-resource constraints were introduced while simultaneously improving resource-profile stability (Banihashemi & Khalilzadeh, 2022). Mean project duration declined from 29.6 months under the resource-constrained schedule to 26.1 months after optimization, recovering approximately 72.9% of the resource-induced increase in project duration. Portfolio makespan decreased from 74.8 to 66.7 months, while mean project lateness declined from 4.3 to 1.4 months. The proportion of projects completed within target dates increased from 41.9% to 78.5%, representing an absolute improvement of 36.6 percentage points. These findings were consistent with earlier resource-leveling and resource-constrained optimization studies reporting that systematic redistribution of activity timing could substantially reduce completion delays without violating precedence or resource-capacity requirements. Earlier studies also emphasized that effective leveling should not be evaluated solely through schedule duration because aggressive compression could simply relocate overloads or generate unstable resource profiles. The present findings demonstrated improvement across both dimensions. Peak resource demand declined from 21,940 to 18,120 resource-hours per month, maximum utilization decreased from 118.4% to 98.6%, and the coefficient of variation in resource demand fell from 23.7% to 13.5%. Capacity-exceeding periods declined by 77.6%, overtime requirements by 64.1%, interproject conflicts by 73.8%, and unresolved conflicts by 86.4%. At the same time, mean utilization increased slightly from 82.6% to 84.1%, while idle capacity decreased from 12.8% to 8.1%. This combination was important because it showed that lower peak demand was achieved through improved temporal allocation rather than through systematic underutilization of available resources (Prayogo et al., 2018). Earlier studies of workload smoothing similarly reported that strong resource-leveling solutions reduced peaks, idle periods, overtime, and resource fluctuations while maintaining productive utilization. Optimization also reduced total float consumption from 64.7% to 28.9%, critical activities from 42.6% to 35.4%, and mean activity displacement from 12.8 to 5.1 days, demonstrating restoration of scheduling flexibility. The large effects for reductions in lateness, resource waiting, float consumption, and overtime further supported the practical importance of these changes. The results therefore extended earlier optimization evidence by showing that a portfolio-level approach could simultaneously improve schedule recovery, workload smoothness, resource utilization, conflict resolution, float preservation, and completion reliability rather than optimizing one performance measure at the expense of the others (Xu et al., 2020).

The subgroup findings demonstrated that resource-constrained scheduling outcomes were heterogeneous and that the severity of deterioration depended strongly on scarcity, network complexity, resource intensity, project priority, and bottleneck exposure. Mean schedule extension increased from 1.7 months under low scarcity to 4.5 months under moderate scarcity and 8.2 months under high scarcity, while float consumption increased from 24.6% to 61.8% and 86.7%, respectively (Pinha & Ahluwalia, 2019). Mean resource waiting similarly increased from 3.1 to 8.7 and 16.4 days. These gradients were consistent with earlier multi-project scheduling studies that identified resource contention as one of the principal determinants of delay when multiple projects competed for the same limited workforce, equipment, or specialist capacity. The partial eta-squared of 0.347 for schedule extension and 0.382 for float consumption indicated that scarcity differences represented large effects rather than minor subgroup variations. Network complexity produced a comparable pattern, with higher-complexity projects experiencing 6.9 months of schedule extension compared with 2.6 months among lower-complexity projects. Earlier studies reported similar sensitivity in dense precedence networks because fewer activities could be displaced without affecting successors, milestones, or alternative critical paths (Shaygan & Testik, 2019). Resource intensity also differentiated lateness and overload exposure, confirming earlier observations that high-demand activities were more vulnerable when resource requirements approached or exceeded effective capacity. Project priority redistributed

these effects across the portfolio. High-priority projects received 91.6% of requested critical-resource allocations within scheduled periods compared with 66.9% among lower-priority projects, producing shorter waiting and greater completion reliability for high-priority work. Earlier priority-based scheduling research similarly showed that preferential allocation protected strategically important projects but could transfer waiting and tardiness to lower-priority work. Bottleneck analysis further demonstrated that four specialized resource categories generated 71.6% of baseline conflicts, with specialist engineering personnel alone accounting for 24.5%. This concentration was consistent with earlier engineering portfolio studies emphasizing that resource scarcity was often localized rather than evenly distributed across all resource categories (Celentano et al., 2019). The strong correlations between resource shortage and schedule extension, resource contention and float consumption, temporal overlap and conflict frequency, and utilization and lateness reinforced these subgroup patterns. Overall, the findings showed that portfolio schedule risk depended less on aggregate resource quantity alone than on where scarce resources were located, when they were demanded, how many projects competed simultaneously, and how much network flexibility was available to absorb allocation changes.

The comparison of exact, heuristic, metaheuristic, and hybrid optimization procedures demonstrated a clear trade-off between mathematical solution quality and computational efficiency (Halim et al., 2021). Exact mixed-integer programming produced the strongest reference solution for computationally tractable instances, with a 17.9% improvement from the constrained baseline and a zero optimality gap, but required a mean computational time of 1,486 seconds. In contrast, the priority-rule heuristic required only 4.8 seconds but produced a smaller mean improvement of 9.6% and an 8.7% optimality gap. These findings closely reflected earlier optimization research in which exact approaches provided benchmark-quality solutions for smaller scheduling instances but experienced rapidly increasing computational requirements as activity counts, resource types, precedence relationships, and portfolio interactions expanded. Earlier heuristic studies similarly emphasized speed and simplicity as principal advantages while recognizing that priority rules could become trapped in locally favorable allocation sequences that did not produce strong portfolio-wide solutions. The genetic algorithm and simulated annealing procedures occupied an intermediate position, producing mean improvements of 15.8% and 14.6% with optimality gaps of 2.8% and 3.6%, respectively (Faris et al., 2018). This pattern was consistent with earlier metaheuristic scheduling studies showing that population-based and neighborhood-search methods could achieve high-quality solutions for complex resource-constrained problems without requiring exhaustive enumeration. The hybrid optimization procedure achieved the strongest practical balance, producing a 17.4% mean improvement, 1.2% optimality gap, 99.5% feasible-solution rate, and mean computational time of 214 seconds. Its resource-demand coefficient of variation of 13.5%, mean lateness of 1.4 months, and penalty cost of \$4.71 million also approached the exact benchmark while requiring substantially less computation. Repeated-run objective variability of only 1.6% indicated that solution quality remained comparatively stable across stochastic runs. Earlier hybrid optimization studies similarly reported that combining global exploration with targeted local improvement could reduce premature convergence and improve final solution consistency. The present findings therefore supported the broader literature suggesting that no single optimization class was universally superior across all criteria (Abualigah et al., 2022). Exact methods remained valuable as benchmarks, heuristics offered rapid approximate scheduling, and metaheuristics improved search quality, whereas hybrid methods provided a particularly effective balance for larger multi-project engineering portfolios where solution quality, resource stability, computational time, feasibility, lateness, and cost had to be considered simultaneously.

Sensitivity and robustness analyses demonstrated that the optimized portfolio schedule remained comparatively stable under moderate changes in activity and resource assumptions but became increasingly vulnerable when effective capacity declined or resource demand increased (Puisseau et al., 2022). A 10% increase in activity durations increased portfolio makes pan from 66.7 to 70.9 months and reduced on-time completion from 78.5% to 70.4%. A 10% reduction in workforce availability produced greater deterioration, increasing makes pan to 72.8 months, maximum utilization to 106.9%, and mean lateness to 2.8 months. The strongest sensitivity was observed when resource demand increased by 10%, producing a makes pan of 73.5 months, resource-demand variability of 18.9%, maximum

utilization of 108.6%, and on-time completion of 63.4%. Earlier robust scheduling studies similarly found that resource-capacity uncertainty could be more disruptive than modest activity-duration variation because reduced capacity simultaneously affected multiple activities and projects requiring the same constrained resource. Conversely, increasing effective resource capacity by 10% reduced portfolio makes pan to 64.1 months and raised completion reliability to 87.1%, reinforcing the importance of effective capacity as a portfolio-level control variable. Robustness analysis across scarcity conditions produced similar evidence (Jung & Kim, 2022). Under high scarcity, optimization maintained a 72.9-month makes pan and 61.8% on-time completion, compared with 81.6 months and 31.7% under the corresponding nonoptimized schedule. Earlier robust and scenario-based scheduling research similarly reported that optimization could not fully neutralize severe resource scarcity but could substantially limit schedule deterioration. Validation results strengthened this interpretation. Across 1,000 repeated simulations, feasible schedules were obtained in 99.3% of runs, mean portfolio makes pan remained near 67.0 months, and 92.6% of benchmark-compatible instances remained within 3% of the best-known solution. Holdout performance also remained close to the primary optimized results, with makes pan of 67.4 months and on-time completion of 76.8%. These findings were consistent with earlier studies emphasizing repeated computational experiments, scenario testing, benchmark comparisons, and out-of-sample evaluation as necessary components of optimization validation (Yang et al., 2020). The limited deterioration between development and holdout conditions indicated that the scheduling gains were not dependent on a single favorable configuration. The results therefore demonstrated that optimized scheduling performance was reasonably robust while also identifying resource-demand escalation and capacity reduction as particularly influential sources of portfolio vulnerability.

The integrated statistical findings demonstrated that the observed optimization improvements were supported by substantial effect sizes, strong predictive relationships, and materially improved completion reliability (Chattapadhyay et al., 2021). The increase from baseline CPM to resource-constrained project duration produced Cohen's $d = 0.94$, while the subsequent reduction from constrained to optimized duration produced $d = 0.83$. Reductions in lateness, resource waiting, activity displacement, float consumption, workload variability, and overtime also generated moderate-to-large or large standardized effects, with float consumption producing $d = 1.12$ and project lateness $d = 1.07$. Earlier quantitative scheduling studies increasingly emphasized the importance of reporting effect magnitude in addition to statistical significance because large project samples could produce small p -values for differences with limited operational importance. The present results demonstrated both statistical and practical importance, since the observed effects corresponded with substantial changes in months of project delay, days of waiting, overtime hours, conflict frequency, and completion probability (Hashemi et al., 2020). Regression analysis further clarified the mechanisms underlying schedule extension. Resource contention was the strongest positive predictor with $\beta = 0.36$, followed by bottleneck severity at $\beta = 0.29$, resource utilization at $\beta = 0.24$, network complexity at $\beta = 0.21$, and temporal overlap at $\beta = 0.19$, whereas available float exerted a protective association of $\beta = -0.27$. The schedule-extension model explained 68.4% of observed variance, demonstrating that combined resource and network characteristics accounted for a substantial proportion of portfolio delay. Earlier empirical studies similarly associated resource contention, high utilization, network complexity, and restricted float with schedule deterioration, although many examined these factors separately rather than within an integrated model. Completion-reliability results provided additional operational interpretation. Greater resource availability increased the odds of target-date completion by 84%, while high project priority more than doubled completion odds. Severe contention reduced completion odds by 58%, and high bottleneck exposure reduced them by 49%. The logistic model achieved 81.2% classification accuracy, with 79.6% sensitivity and 82.7% specificity. These findings reinforced earlier evidence that completion reliability depended on both structural schedule flexibility and effective access to scarce resources. Taken together, the results showed that critical-path behavior, resource allocation, bottleneck exposure, portfolio concurrency, and schedule flexibility were quantitatively interconnected (Gkioni et al., 2019). This study therefore provided an integrated empirical interpretation of multi-project engineering scheduling in which optimization performance was reflected not only in shorter schedules but also in smoother resource demand, reduced conflict

exposure, preserved float, lower lateness, stronger robustness, and substantially improved probability of completing projects within approved target dates.

CONCLUSION

This study concluded that Critical Path Analysis integrated with resource-leveling optimization provided a quantitatively stronger basis for scheduling multi-project engineering portfolios than conventional precedence-based scheduling alone. Analysis of 186 engineering projects containing 8,742 activities, 12,486 precedence relationships, and 684 milestones demonstrated that the baseline portfolio was characterized by substantial network complexity, restricted schedule flexibility, extensive resource sharing, and considerable temporal overlap. Although baseline CPM indicated a mean project duration of 24.8 months and a portfolio makes pan of 62.4 months, incorporation of finite workforce, equipment, and specialist-resource constraints increased mean duration to 29.6 months and portfolio makes pan to 74.8 months. Resource constraints also consumed 64.7% of available float, increased critical activities from 31.8% to 42.6%, delayed 2,746 activities, and reduced target-date completion to 41.9%, confirming that precedence-feasible schedules did not necessarily represent operationally feasible schedules. Resource-leveling optimization substantially corrected these deficiencies by reducing mean project duration to 26.1 months, portfolio makes pan to 66.7 months, mean lateness to 1.4 months, and resource-induced waiting to 3.2 days, while increasing on-time completion to 78.5%. Resource performance improved simultaneously, as peak demand declined by 17.4%, maximum utilization decreased from 118.4% to 98.6%, workload variability declined by 43.0%, overtime requirements fell by 64.1%, and interproject resource conflicts decreased by 73.8%. Subgroup analysis further established that high resource scarcity, greater network complexity, high resource intensity, temporal overlap, and specialized bottlenecks were associated with substantially greater scheduling deterioration. Resource contention emerged as the strongest positive predictor of schedule extension, while available float demonstrated a protective relationship with delay. The schedule-extension model explained 68.4% of observed variance, and the completion-reliability model achieved 81.2% classification accuracy. Comparative optimization results indicated that the hybrid procedure provided the strongest practical balance between solution quality and computational efficiency, achieving a 17.4% mean improvement with a 1.2% optimality gap and 99.5% feasible-solution rate. Sensitivity, robustness, repeated-simulation, and holdout analyses further demonstrated that these improvements remained comparatively stable under changing scheduling and resource conditions. Overall, the findings established that integrating critical-path structure, finite resource capacity, project priority, bottleneck identification, resource leveling, and optimization produced more realistic, stable, and reliable engineering portfolio schedules while materially improving resource utilization and target-date completion performance.

RECOMMENDATIONS

Based on the quantitative findings of this study, engineering organizations should integrate Critical Path Analysis with systematic resource-leveling optimization as a standard portfolio scheduling practice rather than relying exclusively on precedence-based CPM schedules. Project managers should validate baseline schedules against finite workforce, equipment, specialist, and contractor capacities before approving completion targets because the analysis demonstrated that resource constraints increased mean project duration by 19.4% and portfolio makes pan by 19.9%. Particular managerial attention should be directed toward critical and near-critical activities, available total and free float, resource-induced waiting, concurrent project demand, and bottleneck resources because these factors substantially influenced schedule extension and completion reliability. Portfolio managers should establish centralized resource-capacity databases containing current availability, utilization, project assignments, planned demand, overtime, and resource-sharing information so that emerging overloads can be detected before they generate downstream delays. Resource utilization should be monitored continuously at both average and peak levels because the baseline mean utilization of 82.6% concealed peak utilization of 118.4%. Specialized engineering personnel, commissioning teams, heavy lifting equipment, and testing and inspection resources should receive enhanced capacity planning because these four bottleneck categories accounted for 71.6% of baseline interproject conflicts. Resource-leveling procedures should prioritize reducing peak demand, workload variability, overtime, idle capacity, unresolved conflicts, and resource gaps while preserving project priorities and minimizing portfolio

makes pan. The hybrid optimization approach should be preferred for large and complex portfolios where computational efficiency and solution quality must be balanced, given its 17.4% mean improvement, 1.2% optimality gap, and 99.5% feasible-solution rate. Priority rules should remain transparent so that protection of high-priority projects does not create excessive or unmanaged delays among lower-priority projects. Organizations should additionally maintain schedule contingency through adequate float protection and avoid allocating all available flexibility during initial planning. Sensitivity and scenario analyses should routinely test changes in activity duration, workforce capacity, equipment availability, resource demand, project priority, and scarcity conditions before final schedule authorization. Portfolio dashboards should track makes pan, lateness, criticality changes, float consumption, utilization, overload exposure, resource conflicts, overtime, and on-time completion as core performance indicators. Finally, optimized schedules should be periodically recalculated when project scope, activity progress, resource capacity, or portfolio priorities materially change, enabling engineering managers to maintain resource-feasible schedules that support balanced utilization, lower delay exposure, stronger completion reliability, and more effective coordination across simultaneously executed projects.

LIMITATIONS

This study had several limitations that should be considered when interpreting the quantitative findings on Critical Path Analysis and resource-leveling optimization within multi-project engineering portfolios. First, the analysis was based on a final portfolio of 186 engineering projects, 8,742 activities, 12,486 precedence relationships, and 684 milestones; although this dataset provided substantial analytical depth, the scheduling structures, resource configurations, project priorities, and operational conditions represented within the sample might not fully reflect all engineering sectors, organizational environments, or portfolio sizes. Second, the accuracy of the analysis depended on the completeness and reliability of recorded activity durations, precedence relationships, resource assignments, capacity calendars, milestone dates, project priorities, and completion information. Inaccurate baseline estimates or incomplete resource records could have affected calculated critical paths, float values, resource conflicts, and optimization outcomes. Third, resource availability was represented through measurable workforce, equipment, specialist, and shared-capacity constraints, whereas qualitative influences such as individual worker competency, learning effects, managerial judgment, communication quality, subcontractor coordination, and unexpected productivity variation were not fully represented numerically. Fourth, optimization necessarily simplified certain operational conditions by assuming that defined precedence relationships and resource requirements adequately represented scheduling feasibility. In practice, engineering projects can experience weather interruptions, supply-chain disruptions, design revisions, regulatory delays, equipment failures, safety restrictions, material shortages, and emergency changes that may alter activity durations and resource requirements after schedule approval. Fifth, project-priority classifications influenced resource allocation, but priority levels could change during portfolio execution because of contractual, financial, technical, or strategic considerations. Sixth, comparisons among exact, heuristic, metaheuristic, and hybrid procedures were influenced by algorithm configuration, stopping criteria, computational resources, parameter settings, and problem size; therefore, the relative computational performance observed in this study should not be interpreted as universally applicable to every scheduling environment. Seventh, although sensitivity analysis, 1,000 repeated simulations, benchmark comparisons, scarcity scenarios, and holdout validation strengthened assessment of robustness, these procedures could not reproduce every possible combination of uncertainty encountered during actual engineering execution. Finally, statistical relationships between resource contention, bottleneck severity, utilization, network complexity, available float, and schedule outcomes represented associations within the analyzed portfolio and did not independently establish causality for every observed delay. Accordingly, the findings should be interpreted within the defined project, resource, scheduling, optimization, and validation conditions of this study rather than treated as universally fixed performance values for all multi-project engineering portfolios.

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