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Managing Operational Efficiency of Teams in the Field of Property Transportation Services: An Adaptive Model of Dynamic Team Distribution

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ABSTRACT

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Airlines, railways, and public transit agencies schedule crews through mathematical models that cut operational costs and reduce service failures. The moving and relocation industry, with over 102,000 workers at nearly 9,000 registered U.S. carriers, has no equivalent tool. Dispatchers assign crews by intuition, and the resulting mismatches between team capacity and job demands drive property damage, schedule overruns, and workforce turnover. This study introduces the Adaptive Crew Management Framework (ACMF), which scores each job on five complexity parameters (Job Complexity Score), matches the score to a crew configuration (Crew Composition Matrix), and checks each proposed crew member against a rolling fatigue index (Workload Rotation Protocol). Operational records from a mid-size carrier in the northeastern United States were compared across two six-month windows, before and after ACMF adoption. On-time completion rose from 81.3% to 93.7%, damage claims fell by 34%, and quarterly turnover dropped from 28% to 22%. Because ACMF requires only paper scoring sheets and a basic spreadsheet, it is accessible to small carriers that lack dedicated scheduling software.



KEYWORDS

crew scheduling, moving services, operational optimization, adaptive crew allocation, workload balancing, field service management.



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Управління операційною ефективністю бригад у сфері послуг з перевезення майна: адаптивна модель динамічного розподілу команд

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СТАТТЯ

АНОТАЦІЯ

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Авіакомпанії, залізничні перевізники та оператори громадського транспорту використовують математичні моделі планування роботи персоналу, які дають змогу скорочувати операційні витрати та зменшувати кількість збоїв у наданні послуг. Натомість у сфері послуг із перевезення та релокації майна, де у Сполучених Штатах працює понад 102 тисячі працівників у майже 9 тисячах зареєстрованих компаній-перевізників, подібні інструменти практично відсутні. Призначення бригад здебільшого здійснюється диспетчерами інтуїтивно, що нерідко призводить до невідповідності між можливостями команди та складністю замовлення, а відтак — до пошкодження майна, порушення графіків виконання робіт і зростання плинності кадрів. У дослідженні запропоновано Адаптивну систему управління бригадами (Adaptive Crew Management Framework, ACMF), яка передбачає оцінювання кожного замовлення за п'ятьма параметрами складності (Job Complexity Score), співвіднесення отриманого результату з оптимальною конфігурацією бригади (Crew Composition Matrix), а також перевірку кожного запропонованого члена команди за допомогою динамічного індексу втоми (Workload Rotation Protocol). Для оцінки ефективності запропонованої системи було проведено порівняльний аналіз операційних показників компанії середнього розміру, що надає послуги з перевезення майна у північно-східному регіоні США, за два шестимісячні періоди – до та після впровадження ACMF. Результати дослідження свідчать про підвищення частки замовлень, виконаних у встановлені строки, з 81,3 % до 93,7 %, зменшення кількості претензій щодо пошкодження майна на 34 %, а також скорочення квартального рівня плинності персоналу з 28 % до 22 %. Оскільки система ACMF потребує лише використання паперових оціночних форм і базової електронної таблиці, вона є доступною для невеликих компаній-перевізників, які не мають спеціалізованого програмного забезпечення для планування та диспетчеризації робіт.



КЛЮЧОВІ СЛОВА

планування роботи бригад, послуги з перевезення майна, оптимізація операційної діяльності, адаптивний розподіл персоналу, балансування робочого навантаження, управління виїзними сервісними командами.

1. Introduction

Crew scheduling became a formal research problem in the 1960s, when U.S. airlines began using mathematical programming to assign pilots and cabin staff [2]. Integer programming, column generation, and later genetic algorithms carried the approach into buses, ferries, and freight rail [5; 9], cutting crew costs by 4–9% in sectors where it has been tested [7; 12]. What makes these savings possible is a shared structural feature: the timetable. Departure times, route lengths, and seat counts are fixed before planning begins. Without that anchor, the models do not apply.

Moving has no timetable. A grand piano in a fifth-floor walk-up and a set of modular desks on a loading dock land on the same dispatcher's screen as tomorrow's jobs, but they share almost nothing in weight, fragility, access difficulty, or time pressure. The sector sits under NAICS 484210; the Bureau of Labor Statistics [13] puts its average workweek at 33.2 hours, a number that masks pronounced seasonal variation. Summer crews routinely top 50 hours; winter brings underemployment and reduced schedules. Voluntary separation rates run above the transportation-and-warehousing national average year after year [14]. The combination of irregular hours and physically demanding conditions fits the profile that Choper et al. [4] linked to a 20% rise in annual turnover probability across service-sector occupations.

Without a scoring tool, dispatchers rely on experience alone. They review the next day's bookings, estimate crew sizes from memory, and assign available workers without written criteria. The consequences surface daily. At the carrier studied here, a turning point came when a crew lacking specialty experience was sent to a job involving a piano, oversized wardrobes, and a narrow stairwell with no elevator. The absence of a trained piano handler forced improvisation that doubled the expected job time and left the crew physically spent before their second assignment of the day. More routine mismatches follow the same logic: a studio apartment gets three movers who spend half the morning idle, while a four-bedroom walk-up gets two who run out of packing material by noon. Stochastic overbooking models and goal programming cut crew-related costs in cruise shipping precisely because they replaced this kind of informal judgment [7]. A meta-analysis of 259 scheduling studies across industries pointed to a broader pattern: structured allocation tends to outperform ad hoc assignment on both understaffing and overstaffing metrics [16]. Smilowitz et al. [11] framed the cost of mismatches more formally in delivery-fleet research, showing that pairing the wrong team to the wrong route erodes service time gains that took months of driver-territory familiarity to build.

None of the studies above dealt with cumulative physical strain as a scheduling variable. Movers haul sofas up narrow stairwells for eight-plus hours; transit operators remain seated. That difference matters because injury risk in physically demanding occupations does not rise linearly with hours worked. Once recovery gaps between heavy assignments shrink past a threshold, the curve steepens sharply [6]. The Job Demands-Resources model [1] explains why: physical load drains a health pathway while inadequate buffers, such as short-staffed crews or back-to-back high-strain days, simultaneously starve a motivational pathway. Both pathways collapse together. A crew roster built the night before cannot just ask "who is available tomorrow?"; it must also ask "who has already been lifting all week?"

Against this background, the present article proposes the Adaptive Crew Management Framework (ACMF), a structured methodology for crew formation that addresses three interconnected problems: quantifying job complexity before assignment, matching crew composition to that complexity, and distributing physical workload across weekly cycles. Development and validation of the framework draw on operational data from a mid-size USDOT-registered carrier operating in the northeastern United States. The article examines whether a low-technology, criteria-based allocation system can produce measurable improvements in on-time performance, damage reduction, and workforce retention within a sector that currently lacks formalized scheduling tools.

2. Literature Review

Early crew scheduling models optimized a single variable, usually labor cost. More recent work folds in employee welfare, fatigue limits, and service quality as co-objectives. The shift is easiest to trace in airlines. Column generation over set partitioning formulations can technically explore billions of crew pairings, yet real-world data from a major U.S. carrier showed that solver runtime, not model expressiveness, caps solution quality [8]. Rail transit faces a different bottleneck: scheduling and

rostering are usually solved in sequence, which locks in suboptimal duty patterns before individual rosters are even built. An ADMM-based dual decomposition by Zhou et al. [17] attacked both stages at once on a Chengdu metro line and shrank optimality gaps from 34.7% under standard Lagrangian relaxation to 4.2%. Mertens et al. [9] surveyed bus, rail, and airline scheduling together and counted only three published attempts at full three-stage integration (vehicle, crew, roster), all in bus operations. Across every mode studied, the planning chain starts from a timetable that is already fixed. No equivalent anchor exists for industries where job parameters change with each new customer order.

Delivery and last-mile logistics face demand uncertainty closer to what moving companies experience, and the scheduling research there reflects it. Santini et al. [10] ran workforce-sizing experiments at parcel delivery firms and discovered a counter-intuitive result: perfectly predictable shift schedules cost more than slightly flexible ones. Allowing start times to float inside a two-hour band recovered nearly all the savings of fully flexible scheduling without the morale damage of chaotic rosters. Ulmer and Savelsbergh [15] asked a related question for gig-economy platforms: if extra drivers may or may not log in, how many salaried couriers should management pre-commit? Their value function approximation put a price on both over-commitment (idle couriers) and under-commitment (missed deliveries), a trade-off that moving dispatchers face every morning when deciding crew sizes against an uncertain job board. Neither line of research, however, considers that individual jobs might differ in inherent complexity; packages vary in volume, not in handling difficulty.

Worker satisfaction has entered scheduling models mainly through public transit research. Borndörfer et al. [3] added a fairness term to a bus rostering model, distributing unpopular night and weekend shifts more evenly; costs barely moved, but driver satisfaction scores rose. Ernst et al. [5] surveyed the field more broadly, spanning task assignment, shift scheduling, crew scheduling, and tour scheduling. One axis of their classification separates interchangeable from specialized workers. That distinction is acute in moving: a crew member who can create a concert grand piano or secure a 200-kilogram safe onto a stair dolly cannot swap roles with a loader whose training covers only standard carton handling. Van den Bergh et al. [16] reviewed 259 studies and named three scheduling-difficulty drivers: heterogeneous personnel, multi-skill requirements, and unpredictable task durations. Moving operations exhibit all three characteristics, yet none of the 259 studies dealt with household or office relocation.

Physical work and mobile deployment make these scheduling problems harder. Performance benchmarks designed for solo tasks miss the coordination overhead of multi-person lifts, where two workers must synchronize their grip, angle, and pace around stairwell corners and narrow doorways. Gebhardt and Baker [6] documented this gap across warehousing, military, and emergency-service data, finding that individual-task criteria consistently undercount team-based effort. A complementary observation comes from periodic delivery research. Smilowitz et al. [11] tracked what happens when the same driver covers the same territory week after week: route knowledge accumulates, customer familiarity builds, and per-stop service time drops measurably. Bakker and Demerouti [1] connected both findings through the Job Demands-Resources model. Physical demands wear down a health impairment pathway; resources like adequate staffing, clear roles, and recovery days feed a motivational pathway. When resources fall short, both pathways degrade in parallel, raising separation rates and error counts simultaneously. For crews carrying furniture up five flights of stairs over multi-hour shifts, fatigue is not a welfare concern to be addressed after an injury occurs. It is an operational variable that belongs in the dispatch plan.

3. Problem Statement

The tools reviewed above work well when schedules repeat and tasks can be defined in advance. They also acknowledge that heterogeneous workforces, uncertain demand, physical strain, and employee satisfaction interact as constraints. Yet no published study applies these ideas to the moving sector. What sets moving apart from the industries already covered is not any one constraint alone but the fact that all four operate at once: jobs never recur in identical form, workers vary in skill and physical capacity, demand swings daily and seasonally without a stable baseline, and the physical intensity of the work turns fatigue into a safety-critical variable. ACMF translates scheduling principles from these adjacent fields into a method that works without a fixed timetable, using a per-job complexity score as the starting point for crew formation.

4. Methods and Materials

Data for this study were collected at a USDOT-registered household goods carrier operating in a major metropolitan area in the northeastern United States. The company operates a mixed fleet of box trucks ranging from 16 to 26 feet, employs several dozen field crew members, and completes over a hundred residential and commercial moves per month, typically dispatching three to five jobs per day across several simultaneous crew teams. Seasonal peaks between June and September produce volumes 40–60% above the annual baseline, while winter months fall 25–35% below it. Local residential moves constitute the majority of completed jobs, followed by long-distance residential relocations, commercial office moves, and specialty item transport (pianos, artwork, server equipment). Before ACMF implementation, the operations manager reviewed each confirmed booking on the preceding business day, estimated crew size based on the number of rooms listed in the client order, and assigned available workers from a rotating availability board. No written scoring criteria existed for evaluating job difficulty, and equipment allocation was determined by crew leaders upon arrival at the job site rather than during the planning stage.

ACMF was introduced as a three-component system operating sequentially within each daily planning cycle. Every confirmed booking first receives a Job Complexity Score (JCS) calculated from five parameters, each rated on a 1-to-5 scale: Volume Load, Item Sensitivity, Access Difficulty, Travel Distance, and Schedule Pressure. Detailed definitions and scoring anchors for each parameter are presented in Table 1 (Section 4). Scores sum to a composite JCS ranging from 5 to 25, grouped into three operational tiers: Standard (5–11), Elevated (12–18), and High (19–25), with boundary cases reviewed manually by the operations manager. Each tier then maps through a Crew Composition Matrix (CCM) to a prescribed configuration specifying crew size, role allocation, truck type, and pre-staged equipment; specific configurations per tier are reported in Table 3 (Section 4). After CCM produces a candidate crew list, a Workload Rotation Protocol (WRP) checks each proposed member's recent strain history. Jobs add strain points proportional to their tier (1 for Standard, 2 for Elevated, 3 for High), accumulating across a rolling five-day window. When a crew member's cumulative strain reaches 10 points, that individual is flagged for a recovery assignment until the rolling total drops below 7. Strain thresholds were calibrated during a four-week pilot preceding full deployment: initial values of 12 and 9 produced no flags, indicating insufficient sensitivity, and reducing them to 10 and 7 generated flags for approximately 15% of daily assignments, a rate the operations team considered actionable without requiring major schedule restructuring.

Effectiveness was assessed by comparing operational indicators across two consecutive six-month periods: a pre-ACMF baseline (March through August 2024) and a post-implementation period (September 2024 through February 2025). A two-week training phase separated the two periods, during which dispatchers and crew leaders participated in structured workshops covering JCS scoring procedures, CCM application rules, and WRP tracking using standardized scoring sheets. Three categories of indicators were tracked. Operational performance was captured through On-Time Completion Rate (percentage of jobs where total duration did not exceed the client-communicated estimate by more than 30 minutes), Average Duration Deviation (mean difference in minutes between estimated and actual job duration), and Crew Utilization Rate (ratio of billable field hours to total paid hours). Service quality was measured through Damage Claim Rate (filed claims per 100 completed jobs, including any client-reported property damage submitted within 14 days regardless of value or resolution). Workforce stability was assessed through Quarterly Employee Turnover (voluntary and involuntary separations divided by average headcount per three-month interval; each period contained two quarterly measurements, averaged for comparison). Voluntary exit interviews, conducted as standard company practice with departing employees (response rate: 71% across both periods), provided supplementary qualitative data on departure reasons. All data were extracted from the company's existing dispatch management system and payroll records without additional collection instruments.

5. Results and Discussion

Implementation of the Job Complexity Score produced a distribution of assignments across three tiers that varied between periods. During Period A (March through August), the company completed

876 jobs; during Period B (September through February), 791 jobs were completed under ACMF protocols, a volume difference consistent with the seasonal demand pattern described in Section 3. Table 1 presents the five JCS parameters with scoring anchors used by dispatchers during Period B.

Table 1. Job Complexity Score: parameters and scoring anchors

Parameter	1 (Lowest)	3 (Middle)	5 (Highest)
Volume Load	< 300 cu ft (studio)	600–900 cu ft (2-bed)	> 1,500 cu ft (4+ bed)
Item Sensitivity	Standard furniture only	Moderate fragile, partial wrap	Dominant specialty cargo
Access Difficulty	Ground floor, elevator	Mid floor or narrow halls	Walk-up 5th+, tight stairwell
Travel Distance	< 30 min driving	1–2 hours	> 3 hours
Schedule Pressure	Flexible full-day window	Fixed 4-hour window	Multi-party coordination

Source: Formed by the authors.

Retrospective JCS scoring was applied to Period A records to enable tier-level comparison between periods. Table 2 shows the distribution of jobs by complexity tier across both periods.

Table 2. Job distribution by complexity tier across periods

Tier	Period A (n = 876)	Period B (n = 791)
Standard (JCS 5–11)	483 (55.1%)	459 (58.0%)
Elevated (JCS 12–18)	267 (30.5%)	247 (31.2%)
High (JCS 19–25)	126 (14.4%)	85 (10.8%)
Mean JCS	12.1 (SD 4.3)	11.4 (SD 4.1)

Source: Compiled by the authors based on company dispatch records. Period A scores assigned retrospectively.

Period A contained a higher proportion of High-tier jobs (14.4% vs. 10.8%), consistent with the summer peak season falling within that interval. Mean JCS was correspondingly higher in Period A (12.1 vs. 11.4). To account for this compositional difference, performance indicators are reported both as aggregate totals and disaggregated by tier.

Applying the Crew Composition Matrix to scored assignments generated team configurations that differed from pre-ACMF patterns. During Period A, crew size was set almost uniformly regardless of job characteristics: 78.4% of all assignments used a three-person crew, 16.9% used two persons, and 4.7% used four or more. Period B produced a wider distribution aligned with JCS tiers. Table 3 summarizes the CCM default configurations and their application rates during Period B.

Table 3. Crew Composition Matrix: default configurations and Period B application rates

JCS Tier	Crew Size	Role Allocation	Match Rate
Standard (5–11)	2 persons	Lead mover + mover	84.3%
Elevated (12–18)	3 persons	Lead + mover + packer	91.7%
High (19–25)	4–5 persons	Foreman + 3–4 movers	88.0%

Source: Formed by the authors.

Workload Rotation Protocol tracking across Period B recorded a mean daily strain index of 1.7 points per crew member, with 85th-percentile values reaching 2.4. WRP flags (cumulative strain ≥ 10 within any five-day window) were triggered 119 times, affecting 27 of the company's active crew members at least once. Flag frequency peaked in September (28 flags) and October (24 flags), coinciding with the transitional months when residual summer backlog overlapped with the start of ACMF deployment. Recovery reassignments following flags reduced the individual's five-day rolling strain to below 7 within an average of 1.6 working days.

Comparison of aggregate performance indicators between periods is presented in Table 4.

Table 4. Operational performance: Period A vs. Period B

Indicator	Period A	Period B	Change
On-Time Completion Rate	81.3%	93.7%	+12.4 pp
Damage Claim Rate (per 100 jobs)	6.8	4.5	-33.8%
Avg. Duration Deviation	+47 min	+14 min	-33 min
Crew Utilization Rate	64.2%	77.8%	+13.6 pp
Quarterly Employee Turnover	28.0%	22.0%	-6.0 pp

Source: Formed by the authors based on company dispatch and payroll records.

Because Period A and Period B differ in seasonal composition, Table 5 disaggregates the three indicators most sensitive to job complexity by tier.

Table 5. Tier-level disaggregation of key performance indicators

Indicator	Tier	Period A	Period B	Change
On-Time Completion	Standard	89.1%	97.2%	+8.1 pp
	Elevated	74.6%	91.3%	+16.7 pp
	High	58.7%	82.6%	+23.9 pp
Damage Claims /100	Standard	2.1	1.9	-9.5%
	Elevated	9.4	5.7	-39.4%
	High	18.3	10.2	-44.3%
Duration Dev. (min)	Standard	+24	+8	-16 min
	Elevated	+58	+17	-41 min
	High	+91	+29	-62 min

Source: Formed by the authors based on company dispatch records.

Across all three disaggregated indicators, improvements were present within every tier, indicating that the gains are unlikely to be solely attributable to the lower proportion of High-tier jobs in Period B. Magnitude of improvement scaled with tier level: High-tier assignments registered the largest absolute gains in all three metrics, Elevated-tier recorded intermediate gains, and Standard-tier the smallest.

Crew Utilization Rate, measured as aggregate billable-to-paid hours, is not meaningfully disaggregated by tier because individual crew members worked across multiple tiers within each pay period. Aggregate utilization rose from 64.2% to 77.8%. During Period A, 23% of crew leader post-job reports noted arriving at job sites without adequate protective materials; in Period B, this figure fell to 4%.

Quarterly Employee Turnover declined from 28.0% to 22.0%. Exit interviews conducted with departing employees indicated that unpredictable physical strain and inconsistent scheduling ranked among the top three departure reasons for 64% of Period A respondents and 38% of Period B respondents.

6. Discussion

Disaggregation by complexity tier showed a consistent gradient: the more complex the assignment, the greater the performance improvement after ACMF introduction. On-Time Completion for High-tier jobs rose by 23.9 percentage points, compared with 8.1 for Standard-tier. Damage claims on High-tier jobs fell by 44.3%, while Standard-tier claims changed by less than 10%. Duration deviation on High-tier assignments compressed by 62 minutes, versus 16 minutes on Standard-tier work. A plausible explanation is that informal allocation disproportionately underestimates complex jobs. As the uniform crew sizing pattern in Period A shows (78.4% three-person crews regardless of JCS tier), Standard-tier jobs received teams close to their actual requirement, whereas High-tier jobs received crews lacking the headcount, role specialization, or equipment the task demanded. Formalizing the allocation decision through JCS scoring and CCM mapping corrected this asymmetry by directing additional resources precisely where informal judgment most frequently underdelivered.

Comparison with scheduling gains reported in adjacent industries offers a rough benchmark, though direct comparison is limited by differences in sector structure. Steinzen et al. [12] found that integrated vehicle-crew scheduling in public transit reduced total operational costs by 4–7%, while Giachetti et al. [7] reported crew movement cost reductions of comparable magnitude in cruise shipping

through stochastic demand planning. ACMF operates on a different lever: rather than minimizing cost through mathematical optimization of shift sequences, it reduces waste and rework by matching crew composition to job requirements at the point of dispatch. On-Time Completion gains of 12.4 percentage points and Damage Claim reductions of 33.8% are not directly comparable to cost percentages, but they address the moving industry’s primary quality failures, which drive the customer complaint volumes that federal regulators have increasingly targeted through enforcement operations. Ernst et al. [5] noted that scheduling research across industries tends to optimize for cost as the primary objective, with service quality entering models only as a constraint. ACMF inverts this priority: service quality indicators function as the primary optimization targets, while cost efficiency follows as a consequence of better-matched crew sizes and reduced rework.

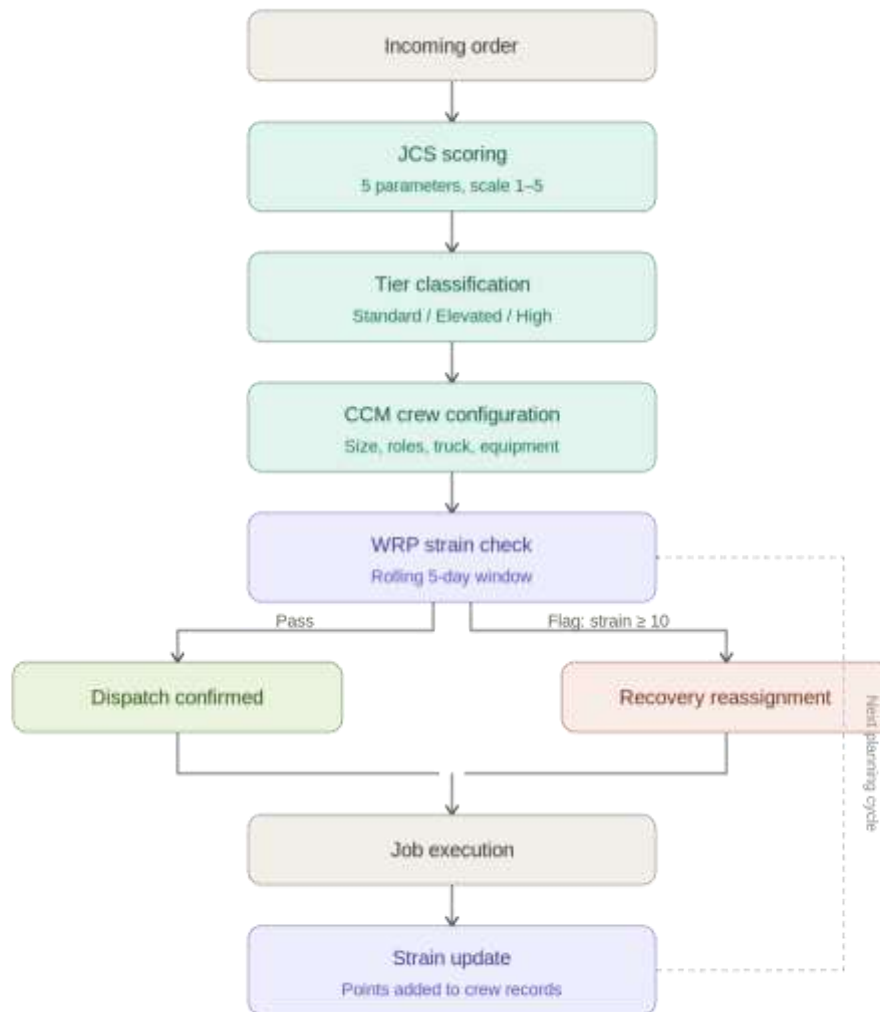


Figure 1. Adaptive Crew Management Framework: operational workflow

Source: Formed by the authors

Equipment readiness shifted visibly under CCM. Section 4 data show that 23% of Period A crews arrived on site missing protective materials they needed; in Period B the figure was 4%. The old process left equipment decisions to the crew leader after the truck had already reached the building. If piano boards or floor runners were back at the warehouse, someone had to make a return trip or improvise with furniture pads. CCM moves that decision to the planning stage: the JCS sub-score for Item Sensitivity triggers a specific equipment checklist before the truck is loaded. Santini et al. [10] saw an echo of this in parcel delivery, where even a narrow pre-planned flexibility window captured most of the efficiency gains of a fully flexible system. Structured preparation at the dispatch desk, even in minimal form, absorbs a disproportionate share of field-level disruption.

Billable hours as a share of paid hours rose from 64.2% to 77.8%. Under the old system a studio move received three workers; under CCM it receives two. The third mover is now available for a separate assignment on the same day. At the complex end, a High-tier job that previously exceeded its estimate by 90 minutes and required a mid-day reinforcement call, pulling a worker off another crew, now finishes closer to schedule because it started with adequate staffing. Ulmer and Savelsbergh [15] quantified this dynamic for gig-delivery platforms: pre-committing the right courier headcount reduced the need for last-minute unscheduled drivers. CCM operates on the same principle. Matching crew size to job complexity during the morning dispatch cycle reduces reactive adjustments later in the day.

Isolating WRP's individual contribution is more difficult because it operated alongside JCS and CCM from the start. The raw numbers: 27 crew members tripped the strain flag at least once across 119 total episodes; each flag cleared in about 1.6 working days. Exit interviews provide circumstantial support. In Period A, 64% of departing workers listed unpredictable physical strain among their top three reasons for leaving; in Period B that share dropped to 38%. Total tonnage moved did not fall. What changed was visibility. Every crew member's five-day strain score sat on a spreadsheet that dispatchers checked each morning. Reaching 10 points triggered a concrete, documented reassignment rather than an informal assurance of lighter duties. Borndörfer et al. [3] observed something parallel in bus transit: spreading unpopular shifts more evenly lifted driver satisfaction even though the total count of undesirable shifts stayed the same. Bakker and Demerouti [1] would classify this as a resource-side intervention under their Job Demands-Resources model. The physical demands did not decrease, but the perceived fairness of how they were allocated appears to have changed.

Several limitations constrain interpretation of these findings and their generalizability. ACMF was tested at a single company operating in one metropolitan area; carriers in rural markets, long-distance specialists, or firms with substantially larger or smaller crews may encounter different constraint structures. Period A JCS scores were assigned retrospectively, introducing potential measurement bias: dispatchers scoring historical records may unconsciously apply knowledge of actual outcomes when rating past jobs. Prospective scoring across both periods would yield more reliable comparisons but was not feasible given the study design. Seasonal differences between periods, despite tier-level disaggregation showing within-tier improvements, cannot be fully neutralized without a randomized or crossover design that is impractical in a live operational environment. WRP applies uniform strain thresholds to all crew members regardless of individual physical capacity, age, or conditioning level. Gebhardt and Baker [6] emphasized that physically demanding job criteria must account for individual variation; ACMF currently does not, and incorporating individualized strain coefficients derived from periodic fitness assessments represents a direction for future development. Finally, CCM permits dispatchers to adjust crew size beyond default prescriptions, an adaptability that is operationally valuable but reintroduces the subjective element ACMF was designed to replace. Monitoring the frequency and outcomes of such overrides is necessary to prevent gradual erosion of framework adherence. Absence of a control group means that external factors, including market shifts, seasonal hiring quality, and natural crew learning effects, may have contributed to the observed improvements independently of ACMF. The findings should therefore be read as indicative of an association between structured allocation and improved outcomes, not as evidence of a causal relationship.

7. Conclusions

ACMF was designed to answer a specific question: whether a criteria-based crew allocation system, operating without specialized software or algorithmic optimization, can produce measurable operational improvements in an industry that has not previously adopted systematic scheduling tools. Tier-disaggregated data across five performance indicators indicate that it can, at least within this operational context. Gains persisted within every complexity tier and every metric category, independent of seasonal job mix. The strongest effects appeared where informal allocation was weakest, on complex, multi-variable assignments that exceed the capacity of intuition-based judgment to assess accurately.

Three methodological contributions emerge from this work. JCS provides, to the author's knowledge, the first published instrument for quantifying the difficulty of individual moving assignments on a standardized numerical scale, converting a subjective dispatcher impression into a repeatable measurement. Where existing scheduling taxonomies classify industries by demand

characteristics and workforce flexibility [5], moving services have been absent from these classifications entirely; JCS and CCM together supply the missing parameters by establishing a documented link between job characteristics and team configuration. WRP extends this contribution into occupational health territory by introducing fatigue tracking into a sector where physical strain has traditionally been managed only after injuries occur, shifting the intervention point from reactive treatment to preventive redistribution.

Each component is deliberately low-threshold in implementation requirements. JCS scoring uses five integer parameters summable on paper; CCM operates as a lookup table; WRP tracks strain points in a basic spreadsheet. No element of the framework depends on proprietary tools, real-time GPS feeds, or machine learning models. For an industry composed predominantly of small and mid-size carriers with limited technology budgets, this accessibility is not a concession to simplicity but a design requirement: a framework that cannot be adopted by a small carrier with limited administrative infrastructure offers no practical value to the sector it targets. Since the close of the observation period, the author has begun applying ACMF principles at a second carrier, where preliminary results suggest that the same stage logic (scoring, matching, strain tracking) transfers to a different crew size and regional market, though formal evaluation of that implementation remains ongoing.

Future research should extend this work along three axes. Multi-carrier validation across different geographic markets and company sizes would test whether JCS parameter weights require regional calibration or whether the current equal-weight model generalizes beyond a single metropolitan context; longitudinal tracking over twelve or more months within such a sample would reveal whether ACMF's effects persist, amplify through organizational learning, or decay as dispatchers develop workarounds. Integration of individualized strain coefficients into WRP, reflecting differences in physical capacity across crew members, would address the framework's most significant limitation and align it with occupational health research that has consistently emphasized individual variation in fatigue response. A third direction is software integration. Most carriers already run some form of dispatch management system; writing JCS and CCM rules into that software would eliminate the paper scoring step, auto-populate crew assignments, and, over time, accumulate enough scored records to recalibrate tier boundaries and parameter weights with statistical confidence.

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