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Staffing Analytics for Critical Infrastructure Uptime

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Abstract

Analytical methods capable of enhancing insights into the operational execution of complex Power & Cooling (P&C) systems are scarce. A framework for applying Workforce Analytics (WFA) to P&C Operations Incident Management is presented, including a description of the processes in Incident Management, identification of relevant data sources, a set of applications, and two case studies. The overall scope focuses on performance variability aspects that are primarily determined in the Triage and Response phase of the incident management process; other phases can also benefit from WFA. Specific applications facilitate efficient P&C Workforce Deployment to reduce both the likelihood and impact of incidents. Aural to the application of WFA is the concept of Mot-Basic-Model. A Mot-Basic-Model represents a (hypothetical) perfect worker in terms of the three critical components of a worker's performance: INTERCEPTION to the incident, CURE execution, and CURE completion.

Mot-basic-model matching analysis addresses the matching of worker's skills and the needs of the incident with a view to cost-effective training and qualification processes. WFA is leveraged to compare the actual incident performance of multiple individualsgroup and/or resource configurations against their respective Mot-Model to identify relative performance gaps and best practices for continuous process improvement. The above Analytical methods and metrics also support Recovery and Post-Incident Review functions of the Incident Management process. A nuclear plant cooling system incident database illustrates the practical application of WFA; parallel directions are being followed for the Power Infrastructure of an Internet data center.

Keywords: Power and cooling operations management; power production; data-center; Datacenter; incident management; workforce analytics; open-source tools and techniques; Artificial Intelligence for IT Operations (AIOps); Information Technology Infrastructure Library (ITIL); Computerized Maintenance Management System (CMMS); environmental, health, safety, and community (EHSC) regulatory compliance.

1. Introduction

Cloud and other IT services are increasingly delivered in large data centers, where Power and Cooling (P&C) Operations maintains the electrical supply and cooling infrastructure. Outage incidents in P&C Operations are infrequently detected, swiftly fixed, and often overlooked. Power and Cooling Operations are not revenue-generating, and staff are recruited and scheduled just to meet the peak load. Using incidents, Workforce Analytics improves incident management, enhancing service affordability and reducing operational risk.

The key steps in the Cloud service incident Management process—Detection and Reporting, Triage and Response—are described. Detection and Reporting rely on trained, alert staff, supported by Command, Control, and Monitoring Systems. Triage and Response resources are supplied by Staffing and Scheduling Optimization (to meet peak load), Skill-Match Matching (for

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timely Support), and Benchmarking and Continuous Improvement Insights (for personnel effectiveness). Seven Analytics applications are outlined: training needs; near real-time recovery support; improvement proposals; performance appraisal data; downtime cost modelling; hazard exposure and mitigation; and CMMS tickets closed-freeze time.

Framing data governance and ethics ensures trustworthiness. Data from Corporate IT, CMMS, shift logs, staffing schedules, surveys, and Command, Control, and Monitoring Systems supports detection, triage and recovery, post-incident analysis, and continuous improvement. Combining Information Management and Process Analytics fosters investigation of incident Management question.

1.1. Scope and Objective

Information Technology Infrastructure Library guidelines define incident management as an unplanned, service-affecting event that is resolved via a defined workflow. Workforce Analytics helps improve incident management across a wide range of existing service domains in Power and Cooling Operations, including data center services, nuclear facilities, pharmaceutical production, and critical process infrastructure. The analytics solution relies on the current state of the operation and the incident management framework defined in Information Technology Infrastructure Library and Process-Pad publications, encompassing detection and reporting, triage and response, recovery and post-incident review. Improved incident recovery and continuous service improvement are also part of an evidence-based discovery of staffing, scheduling, and training needs.

Data governance, privacy, ethics, and quality control concerns for the handling of personally identifiable information are paramount throughout. Current research extends Incident Management and Service-Related Analytics in support of Power and Cooling Operation Services. Early directions explore a broad set of relevant Power and Cooling Operations Service domains that rely on IT Infrastructure Library Compendium definitions and incorporate Service-Related Work for proactive staffing and scheduling optimization, Critical Infrastructure Control System season-specific Skill Plan coverage, Safety Equipment Pre-mitigation Training, and Post-Incident Review Service-Related Work Performance Brick.

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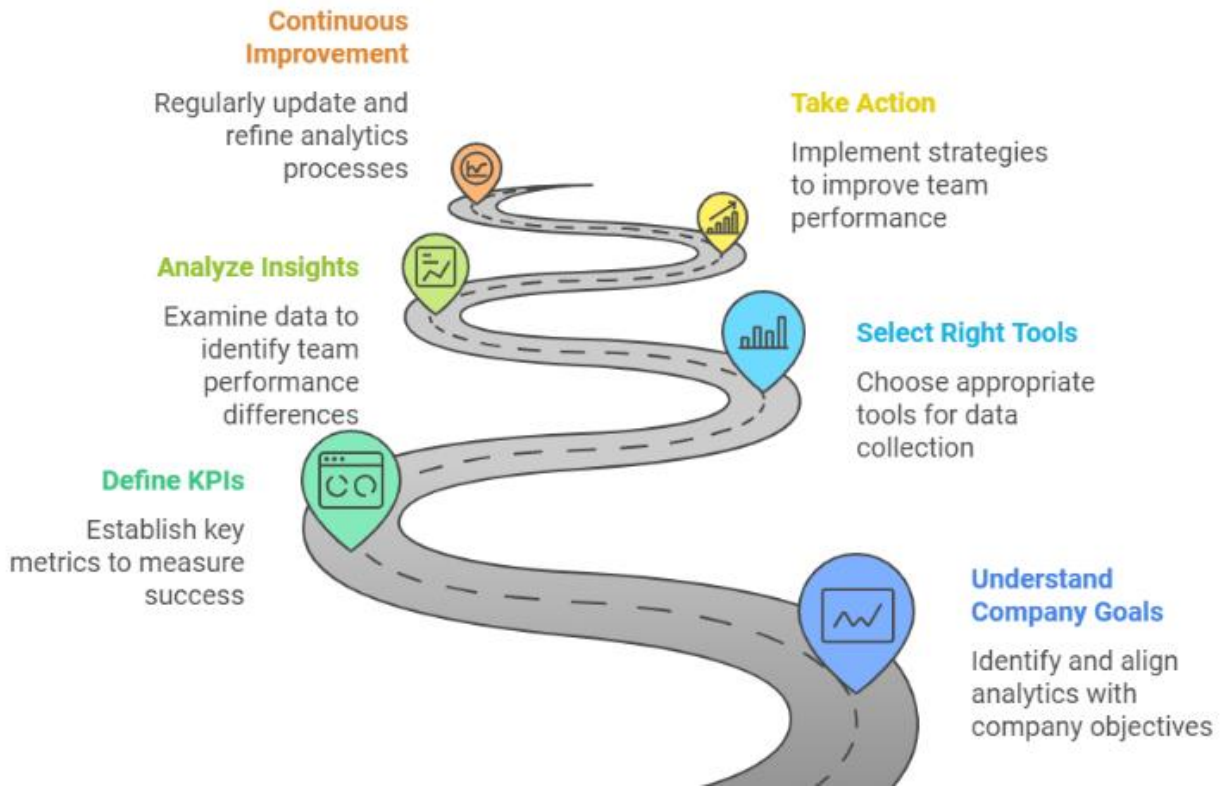

Fig 1: Workforce Analytics for Improving Incident Management

1.2. Research design

Research in information systems (IS) examines the development, adoption, and impact of computing and communications technology, as well as the emerging possibilities posed by technology-enabled change. A study of workforce analytics for improving incident management in Power and Cooling operations associated with data centres or critical infrastructure adds to the directions of IS research concerned with the business use of analytics and social computing out of concern for the impact of such change on people. A framework for Power and Cooling Operations presents the generation, use, and reporting of operational data as business intelligence to improve workforce decision making, leading to reduced outages and service cost. These concerns follow the definitions of incident and incident management set out by the IT Infrastructure Library (ITIL), albeit used in the context of management of Power and Cooling Operations.

ITIL records the following three processes: detection and reporting, triage and response, and recovery and post-incident review. Each of the processes can benefit from a Workforce Analytics capability that aids in decision-making. Staffing and scheduling required to staff the operation, skill-set matching of the pool of workers assigned to the process with the workers' skills then

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reveals possible training needs of the group. Performance benchmarking of the process then aids continuous improvement. Together these applications work toward reducing the frequency of incidents and outages and costs of service. Two case studies consider Workforce Analytics applied to Power and Cooling Operations. The first is based on power supply and cooling of a data centre serving enterprise and government applications, while the second considers cooling water supply to the safety systems of a nuclear power station.

Equation 1: Multinomial logistic model for shift-group assignment

Step 1: Define the outcome

Let the shift-group category be

$$Y \in \{1,2,\dots,K\}$$

where $K$is the number of shift groups.

Let

$$x = \text{time gap between incident date and assignment date}$$

Step 2: Model each class score

For multinomial logistic regression, assign a linear score to each class k:

$$\eta_k = \beta_{k0} + \beta_{k1}x$$

where

- β_{k0}= intercept for shift group k
- β_{k1}= effect of the time gap on membership in group k

Step 3: Convert scores into probabilities

Probabilities must be positive and sum to 1, so exponentiate and normalize:

$$P(Y = k \mid x) = \frac{e^{\eta_k}}{\sum_{j=1}^{K} e^{\eta_j}}$$

Substitute η_k:

$$P(Y = k \mid x) = \frac{e^{\beta_{k0}+\beta_{k1}x}}{\sum_{j=1}^{K} e^{\beta_{j0}+\beta_{j1}x}}$$

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Step 4: Use a reference category form

Pick shift group Kas the baseline. Then for $k = 1, \dots, K-1$,

$$\log\left(\frac{P(Y = k \mid x)}{P(Y = K \mid x)}\right) = \beta_{k0} + \beta_{k1}x$$

This comes from:

$$\frac{P(Y = k \mid x)}{P(Y = K \mid x)} = \frac{e^{\beta_{k0}+\beta_{k1}x}}{e^{\beta_{K0}+\beta_{K1}x}}$$

If baseline coefficients are set to zero, $\beta_{K0} = \beta_{K1} = 0$, then

$$\frac{P(Y = k \mid x)}{P(Y = K \mid x)} = e^{\beta_{k0}+\beta_{k1}x}$$

2. Literature Review

The literature review is presented in three subsections. The first discusses analytical methods and related metrics used to assess incidents and identify operational improvement opportunities. The second explores incident recovery and post-incident review practices. Finally, the incident management processes for systems in the power and cooling domain are outlined.

A variety of analytical methods and metrics can be used to assess historical incidents, identify the underlying causes, and highlight opportunities for improvement. Analysis may use the associated tickets and supplementary data to focus on areas such as incident frequency and duration, the repeatability of incidents, major incident causes, the relationship between incident recovery time and remediation effort, and the associated financial costs. Such analyses can reveal a breadth of insights into the performance of incident management processes, covering topics like suitability of current staffing, scheduling, and skill-mix arrangements; training needs to strengthen skills in preparation for situations with low recovery times and high remediation efforts; and the relationship between performance and skilled vendor resources. Such analyses can then serve as inputs to benchmarking and continuous improvement efforts.

Phase	Description	Key Activities	Data Sources
Detection & Reporting	Identification and communication of incidents	Monitoring, alerting, logging	Monitoring systems, logs

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Phase	Description	Key Activities	Data Sources
Triage & Response	Prioritization and assignment of resources	Risk assessment, escalation, resource allocation	CMMS, staffing data
Recovery	Restoring system functionality	Repair actions, decision-making	Incident records
Post-Incident Review	Analysis and improvement	Root cause analysis, feedback collection	Surveys, reports

Table 1: Incident Management Process Table

2.1. Analytical Methods and Metrics

Two analytical methods improve incident data: Recovery Time Analysis (RTA) quantifies efficiency, and Post-Incident Review (PIR) assesses culture. RTA tracks steady-state periods between outages and estimates recovery rate based on historical data and key decisions made during recovery. PIR identifies factors enhancing or debilitating incident management using a pre-pilot questionnaire and leader-derived attributes of a positive culture.

Recovery Time Analysis (RTA) quantifies an organization's incident management efficiency. The method determines the average time it takes to recover from outages, particularly exploring how people and decisions factor into the result. To achieve a steady-state condition, incidents must not occur so rapidly that insufficient data are available to train a recovery team or that the workload exceeds the team's ability to manage incidents effectively. RTA assesses the average recovery rate, determining how committed the organization is to solving incidents through analysis of recovery time intervals and key decisions made during the recovery process.

Analytical methods, such as Post-Incident Reviews (PIR), can assess organizational culture's impact. A PIR is an analysis of a specific incident and its factors, addressing whether they made the incident easier or harder to manage. A PIR can consist of a questionnaire distributed to dedicated staff and project leaders before a pilot of any change to a system, with the responses rated for score, or even as informal discussions or brainstorming with a small group. Analysis can then seek whether factors of positive culture, such as collaboration, support, and candid reporting, are present and assess the importance attached to the presence or absence of the identified factors.

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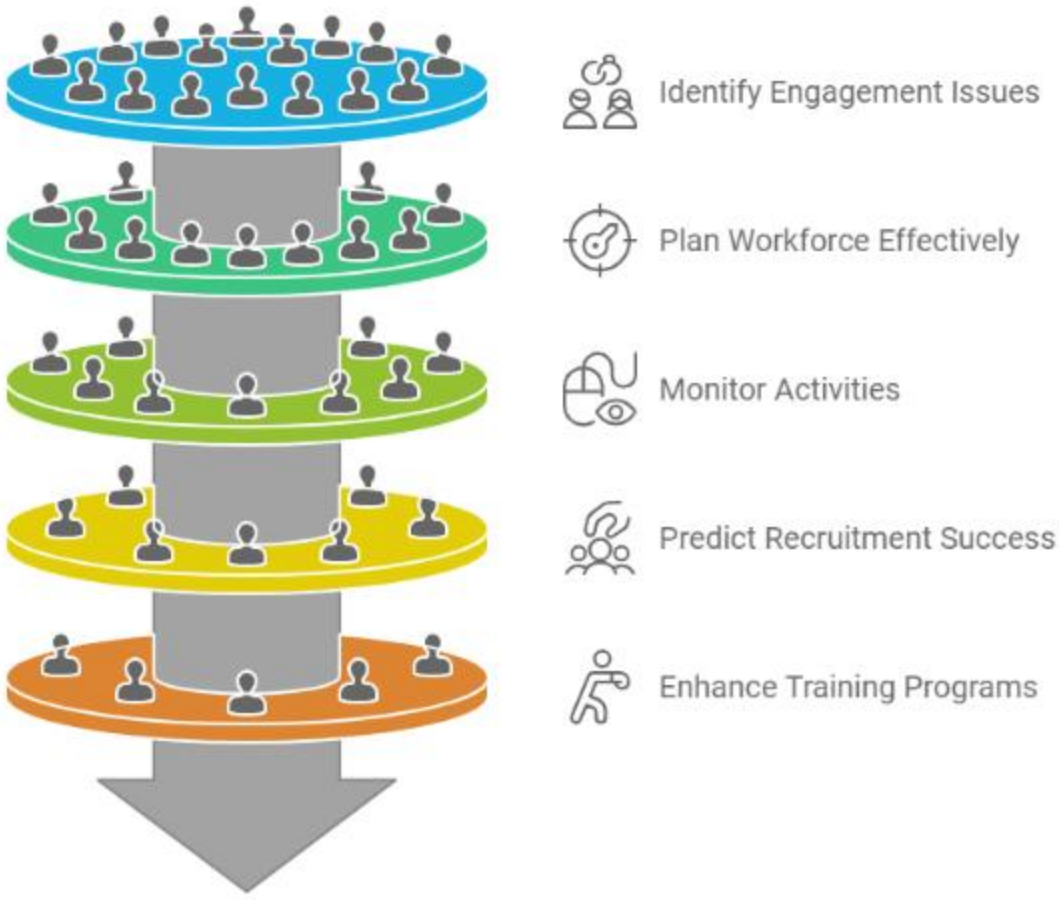

Fig 2: Workforce Analytics

2.2. Recovery and Post-Incident Review

Recovery and post-incident reviews focus on analyzing the root cause of incidents, improving staff performance, and adopting preventive measures. Successful action plans should ensure that all risks and mitigation measures are verified prior to changing the configuration. Most incidents should be known risks, and the cost of identified risks should be reduced to a level the organization is willing to accept for the business outcome it enables.

Workforce analytics can help operational teams reduce incidents and improve recovery by identifying preventive actions, but these analytics are rarely used. If data can be reinvented, considered a strategic asset, and governed properly, future incidents will be avoided; therefore, the cost of recovery will drop to its variable component associated with burden management. Junior staff

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may then be overloaded and autumn training can focus on bridging knowledge gaps. However, the fact that an incident is detected does not mean it is always known.

The optimum balance between staffing and relevant technology remains delicate and the Bermuda triangle of supporting systems is one example. Repeated detection and high variability of response time compromise recovery, even if the supporting technology and business impact are considered. Understanding these combinations for staffing and response time, and detecting recovery thresholds, should enable skill–moc matching and proper training needs. Static performance plots improve the redundancy of review processes and help ensure that a recommendation evolves into a proper preventive action.

Equation 2: Staffing requirement from forecast incident volume

Step 1: Define expected workload

Let

- $\widehat{N}_t$= predicted number of incidents in period t
- $\bar{h}$= average labor-hours required per incident

Then total required workload-hours in period $t$are

$$W_t = \widehat{N}_t \bar{h}$$

Step 2: Define effective staff capacity

Let

- H= paid hours per worker in the period
- α= utilization factor, $0 < \alpha \leq 1$

Then effective productive hours per worker are

$$C = \alpha H$$

Step 3: Divide workload by capacity

If each worker contributes Ceffective hours, then the number of workers required is

$$S_t = \frac{W_t}{C}$$

Substitute $W_t = \widehat{N}_t \bar{h}$and $C = \alpha H$:

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$$S_t = \frac{\hat{N}_t \bar{h}}{\alpha H}$$

Step 4: Round up

Because staff count must be an integer:

$$S_t^* = \left\lceil \frac{\hat{N}_t \bar{h}}{\alpha H} \right\rceil$$

3. Framework for Workforce Analytics in Power and Cooling

An ethical framework addressing data governance and privacy and the integration of toolsets, platforms, and business processes maintains focus on capturing and utilising data to support operations in real time and develop predictive and prescriptive analytic capacity. The objectives focus on acquiring the necessary quantity and quality of incident data to support Analytics for the Improvement of Incident Management in Power & Cooling Operations, thereby reducing the risks to mission-critical equipment. A data lake supports many forms of data sources while facilitating data synthesis to enable Multivariate Quality Control and Combination and Recovery Analysis. The approach is underpinned by data integration via an Enterprise Resource Planning system (SAP) combined with the integration of operations support from Computer Information System (CIS) (such as Remedy) and APM, CMMS, and APM scheduling, system monitoring, and Physical Security Information System (PSIS).

The concentration of analytics on the meaningful, significant incidents for operations is viewed in management and supervisory capacity, considering both temporal and geographical scheduling. Effectiveness is reviewed through skill-matching capability, identifying technical know-how or certification gaps, and the realisation of improvement investment needs and tracking of completeness. Performance benchmarking and monitoring examine service time by incident and service activity type while providing a benchmarking framework for internal, across-location, and external performance comparison. Developers, Support Staff, and Vendor-Supported groups deliver staffing resources, with performance monitoring considered within review and continuous-improvement practices.

Equation 3: Recovery Time Analysis and average recovery rate

Step 1: Define recovery time for each incident

For incident i,

- t_i^{start}= outage start time
- t_i^{end}= service recovery time

So recovery duration is

$$T_i = t_i^{end} - t_i^{start}$$

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Step 2: Compute mean recovery time

For $n$incidents, average recovery time is

$$\text{MTTR} = \frac{1}{n}\sum_{i=1}^{n} T_i$$

Substitute $T_i = t_i^{end} - t_i^{start}$:

$$\text{MTTR} = \frac{1}{n}\sum_{i=1}^{n} (t_i^{end} - t_i^{start})$$

Step 3: Define recovery rate

If "rate" means amount of recovery completed per unit time, then for normalized full recovery of one incident, rate is inverse time:

$$r_i = \frac{1}{T_i}$$

Average recovery rate across incidents:

$$\bar{r} = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{T_i}$$

A simpler system-level proxy is inverse mean recovery time:

$$\bar{r}_{\text{sys}} \approx \frac{1}{\text{MTTR}}$$

3.1. Data Governance and Ethics

In critical operations, incidents remain inevitable due to system and human-factor failures. Every incident that occurs requires proactive triage for detection, reporting, and response; such processes consume resources that ultimately constrain an operation's core capabilities. This bandwidth can, however, be optimized through predictive analytics. By leveraging historical incident-management data, predictive tools can recommend more efficient and effective staffing—suggesting skill sets and experience to support schedules for all phases of detection, triaging, response, recovery, and post-incident review. Such insights not only link

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workload and staffing levels but also indicate areas of training focus to address under-utilised skills or capabilities and enhance performance through benchmarking and ongoing improvement.

These opportunities to optimize the workforce-incident-management interface in Operations Analytics can be applied to any 24 / 7 operation requiring skills to monitor and react to incidents — from Power & Cooling operations in data centres to cooling systems at industrial production facilities, to pressurised water reactor nuclear plants. Yet, derivation of best-fit analytics demands attention to the specifics of each organisation and appropriate ethics balance, as set out in this component of a series referencing recent first-principal research undertaken for an SLT project at a leading North American university in partnership with a tier-one national service partner.

3.2. Data Sources and Integration

Integration of data from different sources enhances the effectiveness of Workforce Analytics, particularly in relation to defining, quantifying, and benchmarking incident management performance. The primary data source for incident management is the digitalized ticketing database where incidents are logged. Disaster Recovery (DR) data from internal audits assesses plan effectiveness and identifies areas for improvement. DR test process data aids need identification, while the Learning Management System (LMS) reveals training and qualification requirements. Knowledge management databases suggest the required expertise for Incident Response teams in DR tests.

Data-driven performance benchmarks are established similar to Mean Time To Recover (MTTR) and Mean Time Between Failures (MTBF). Operational data, aligning with Power Distribution and Storage Data, identifies resource requirements for various tests. Continual improvement principles apply during the review of benchmarks, enabling a cycle of evaluation and enhancement of skills, KPIs, and testing frequency.

Fig 3: Data Integration

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4. Incident Management Processes in Power and Cooling Systems

All incidents in power and cooling systems, such as uncontrolled temperature, humidity, or pressure excursions, decreased performance or degradation of equipment or services, and even alarms or alerts, require a management process to maximize the probability of restoring operations safely, reliably, and efficiently. The process has four primary phases: detection and reporting; triage and response; recovery; and post-incident review (PIR).

Detection and Reporting. The initial detection of an incident and the reporting by the first person observing it initiate the incident management process. Regulators and senior management expect a low tolerance for risk, and hence there is a preference for over-reporting. Advanced monitoring and diagnostic tools can help facilitate fast detection, pre-define alerts by severity levels, and trigger alerts to responsible parties through different channels, such as email, short message service, or a mobile application. However, the incident management workflow still relies primarily on human beings, as responsibility and ownership of the environments lie with the Operations teams.

Triage and Response. The risk assessment principle implies that resources should focus on the classes of incidents with the highest associated risk. Like any emergency response team, Operations groups have skilled personnel at hand who are trained to act quickly according to predefined escalation procedures. For less severe incidents, Operations groups need to perform a triage function prior to action. For example, when at least two critical infrastructure systems are affected simultaneously—such as power supply, cooling, connectivity, or monitoring—as the incident will impact service, it will need to be escalated immediately. Alternatively, for less serious incidents, the escalation should be performed only in cases when a rapid response would accelerate recovery.

4.1. Detection and Reporting

Incident detection is the identification of an anomaly or condition that results in a loss of resiliency in the supporting infrastructure or plant process. The ability to detect incidents before they directly affect resiliency is dependent on system monitoring, alarming capabilities, awareness of the capability of the supporting infrastructure, and the knowledge of the personnel responsible for detecting and responding to incidents.

An incident can be detected in two ways: either automatically at the system or by operations personnel monitoring the data. Timely reporting of incidents detected by an authorized responder is critical to reducing recovery time. To minimize the impact of incidents on system resiliency, both detection and reporting should be as timely as possible. A short detection and reporting time provides the opportunity for rapid triage and response and a smaller impact area.

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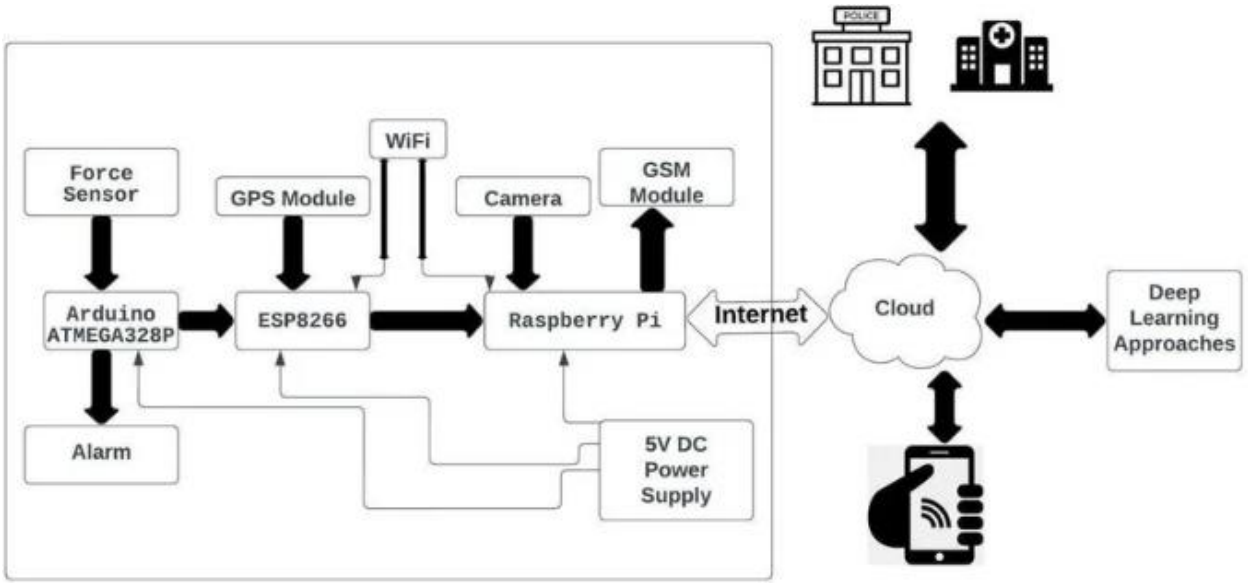

Fig 4: Detection and Reporting System

4.2. Triage and Response

The urgency of incident triage and response processes heavily influences the success of any incident management system. In Power & Cooling systems, the majority of incidents are considered minor, although the processes involved in their management often require substantial resources and time. Considering the large and complex nature of their operations, it is of utmost importance for Power & Cooling organizations to either accurately predict or delegate resources to these incident categories to reduce the time needed for incident resolution.

A comprehensive categorization of incidents is therefore essential. Operations with sufficient resources available can utilize both in-house staff and 3rd party organizations with the relevant equipment and training to minimize the time to repair. For systems with additional complexity, priority should be given to Power & Cooling sites that require support from central functions. Furthermore, with an increased focus on Health Safety and Environment aspects for incident resolution, triage, and response, the important skills identified should be periodically assessed and validated to ensure a good skill-matching for the most critical incidents within Power & Cooling.

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Application Area	Purpose	Output/Benefit
Staffing & Scheduling Optimization	Ensure availability of skilled personnel	Reduced downtime, cost efficiency
Skill-Moc Matching	Match worker skills with incident requirements	Improved response quality
Training Needs Identification	Identify skill gaps	Targeted training programs
Performance Benchmarking	Compare workforce performance	Continuous improvement
Downtime Cost Modelling	Estimate financial impact	Cost optimization
Hazard Exposure Analysis	Identify risk exposure	Safety improvements
CMMS Ticket Analysis	Track resolution efficiency	Faster closures

Table 2: Workforce Analytics Applications Table

5. Workforce Analytics Applications

The business of operation and maintenance of a Power and Cooling infrastructure has its operational demand cycles and the sensitivity associated with these cycles suggest that resources should be available and their skills should be fresh. Workforce analytics techniques can assist with the fulfilment of these needs (staffing and scheduling), can highlight the areas where improvement can be made in the skills of the workforce (skill–moc matching and training needs), and can allow identification of the appropriate performance metrics so that identification of underperformance becomes possible (performance benchmarking and continuous improvement). These areas are explored in the following subsections, using archive data from two case studies, one from the Power system and the other from the Cooling system.

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The first area of application is the optimization of staffing and scheduling, achieving better availability of resources and a reduction in operating cost. This is followed by Skill–Moc matching and Training Needs, using skills status and motion data associated with the Nuclear Power station to generate recommendations for skill refreshers. The last application area is Performance Benchmarking and Continuous Improvement, using the incident data from the Data Center Power infrastructure to create actionable metrics that can be utilized during post-incident reviews (PIR). Addressing these areas within Workforce Analytics can assist with workforce–resilience for an organization's Power and Cooling Operations.

5.1. Staffing and Scheduling Optimization

The optimization of staffing and scheduling in Incident Management processes for Power & Cooling Operations is based on the premise that improving the temporal availability of personnel with past incident exposure will improve incident resolution times. With sufficient incident data accumulated over time, temporal patterns in new incidents can be discerned and incident volumes across different shift groups can be compared. Using these sources of information, predictive models are developed to forecast the volume of incidents in a supervisory control and data acquisition (SCADA) Power display and, subsequently, the personnel requirements to effectively manage these incidents.

Multinomial logistic regressions are employed to model the relative likelihood of being assigned to a SCADA Power shift group as a function of the time between the incident and the date the group member was assigned to the shift. Other avenues available to an organization for increasing the temporal exposure of workforce members to incidents are also explored. These include potential skill-set training need identification through a matched incident analysis process and performance benchmarks based on both team dynamics and post-incident reviews.

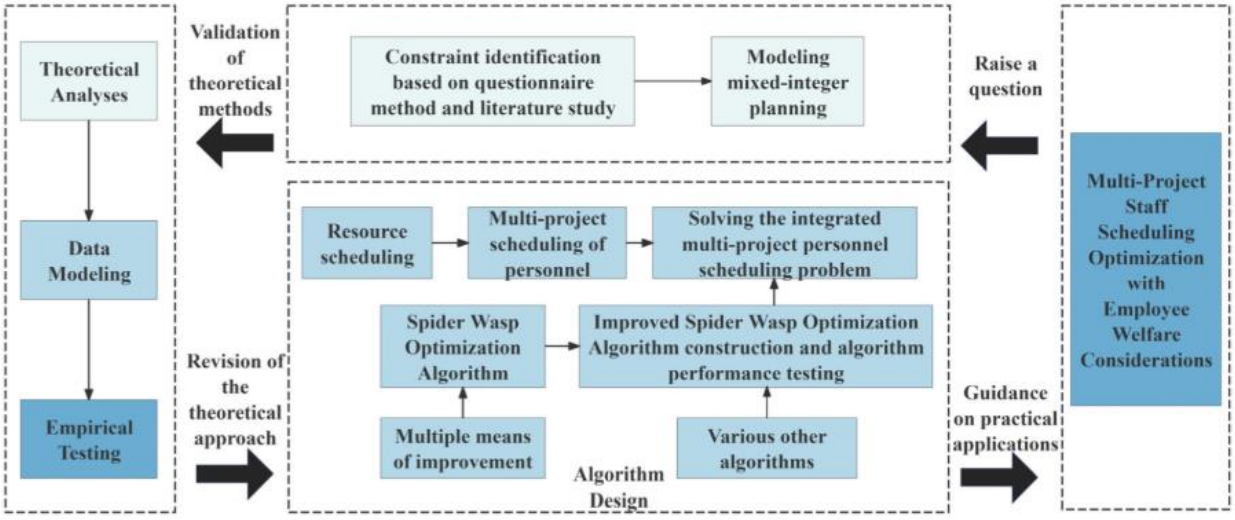

Fig 5: Staff Scheduling Optimization

5.2. Skill-Moc Matching and Training Needs

Analysing historical incidents improves service delivery through skill-matching and training needs identification.

Skill-Moc matching follows an 'Incident or Problem-Solution-Moc-Moc' structure. Mocs are created for incidents types and for significant or frequently occurring problems. An incident record sources the moc, listing resources necessary for recovery. Service providers use the moc to select Fte. When skill-level mismatching occurs, the fte's skill matrix is updated and training needs identified. Resources can be shifted to a new moc-threshold level for future incidents by selecting training content.

Training needs can also arise from a designated moc unable to cater for the last incident; agent visits required escalation, revealing lack of skill. Assistant 'Training Needs' reports for identified Ftes highlight gaps in those agent's specific mocs, showing prerequisite mocs or a higher moc-threshold level. A more empowered 'Training Needs' report raises 'Moc-Moc-Missing' alerts and periods unserviced due to skill-level incapacity.Resource management with a training and recruitment workflow enhances the Service provider's future incident handling.

Equation 4: Skill–MOC matching score

Step 1: Represent required incident skills

Suppose an incident requires $m$skill items. Let

$$r_j = \begin{cases} 1, & \text{if skill } j \text{ is required} \\ 0, & \text{otherwise} \end{cases}$$

Collect them in a requirement vector:

$$\mathbf{r} = (r_1, r_2, \dots, r_m)$$

Step 2: Represent worker capability

For worker w, let skill readiness be

$$s_{wj} \in [0,1]$$

where

- 0 = no capability
- 1 = fully qualified
- intermediate values = partial qualification

So worker w's skill vector is

$$\mathbf{s}_w = (s_{w1}, s_{w2}, \dots, s_{wm})$$

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Step 3: Compute matched coverage

Only required skills matter, so matched contribution is

$$\sum_{j=1}^{m} r_j \, s_{wj}$$

Step 4: Normalize by total required skills

Total requirement weight is

$$\sum_{j=1}^{m} r_j$$

Hence normalized match score is

$$M_w = \frac{\sum_{j=1}^{m} r_j \, s_{wj}}{\sum_{j=1}^{m} r_j}$$

This yields $0 \leq M_w \leq 1$.

Step 5: Define training gap

A natural mismatch or training-gap score is

$$G_w = 1 - M_w$$

5.3. Performance Benchmarking and Continuous Improvement

As corporate priorities shift from growth and profitability to sustainability and efficiency, Fleet Duty Lead's power and cooling service request volume is expected to decline further—possibly changing incident profiles as well. Typical Department of Energy power plant models, including nuclear plants, rely on other methods (thermochemistry, facile thermochemistry, etc.) for economic staffing studies, so Fleet Duty Lead is left with few benchmarking approaches. That scarcity makes even incidental staffing inefficiencies difficult to quantify or target for correction, and infrequent-use staff profiles z- or u-shaped risk understated. Historical incident analysis helps—but solely retrospectively, with no consequences for prior mismatches. A retrospective, computation simulation-based benchmarking and continuous-improvement framework draws on workload determinants.

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Quantitative workload determinants are not limited to atmosphere or spring-break travel. Any factor that clearly reduces workload can suggest potential overtourism and highlight volume-control dangers. On-duty model-clocked past separation of areas of skill concentration offers skill-profile linking and requisite-moc-matching opportunities. A history of controllable short-term factors appearing in incidents could provide temperature-departure, meteorological, special-event, or other profiles around which deeper skill-set, skill-use, or journeyman-skill-differential support-staff pooling could be set up. Reliable simulations of incident-detection delays would allow computation of historical detection-and-launch delay costs. The ability to determine costs associated with simple, stable activity profiles and undertakings of short duration, good predictability, and limited need for particular skill groups additionally highlight risk-sharing opportunities.

6. Case Studies

Two case studies illustrate how these principles are applied to the staffing and operation of cooling systems in a nuclear power plant and a data center.

Case Study A: Nuclear Plant Cooling System

The cooling system of a nuclear power plant poses stringent reliability requirements, with any failure during operation or a loss of redundancy during hot standby likely resulting in a shutdown. To meet this critical availability requirement, the operator implemented Availability Management Procedures supported by risk-based quantitative analysis. This approach integrates workforce analysis within Incident Management; evaluates the likely nature, number, and duration of incidents; and allows an assessment of the required level of staffing and the most cost-effective allocation of resources.

Analysis of the coolers operated during a period of several years revealed that fewer—sometimes much fewer—than the available units were actually in operation. The tracking of resources used provided an empirical database for assessing the connections, skills, and knowledge of all the personnel who could be called to resolve incidents. In addition, the review of incidents formed the basis for validating and complementing training. The net benefit of these analytical areas of Workforce Analytics was a significant reduction in costs, together with the increased confidence that the Operational Availability requirements were being achieved reliably.

Case Study B: Data Center Power Infrastructure

In the power infrastructure of a data center, a growing volume of work on the supply chain and non-operation-related customer jobs started to affect Incident Management time and performance. With retrospective analysis revealing year-on-year increasing incident volume and minor resource adjustment made to respond to that volume, a simple communication tool was created to summarize and rank the resourcing power and cooling incidents. Risk priority numbers (RPNs) were assigned to each incident on the basis of frequency, severity, and time consumption. These RPN analyses, regularly updated, then became the basis for targeted training and upskilling. Over time, this developed more known connections for operations support and responded to the volume of non-Ops work.

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The previous year's data allowed a suitable level of Ops people to be scheduled, but as it was based on that year's volume, use year-on-year would inevitably introduce resourcing gaps or excess. The newly communicated tool, fed with Incident times, saved overt excessive scheduling that the previous year's volume would have suggested. Satisfaction from both operations and customers improved, and the two-year travel plan introduced to upskill senior engineers was funded through better management of other people's time and collated risk-rewards.

Equation 5: Risk Priority Number (RPN)

Step 1: Define the three factors

For incident i, let

- F_i= frequency score
- S_i= severity score
- T_i= time-consumption score

These are usually ordinal scores, for example from 1 to 10.

Step 2: Combine them multiplicatively

The standard RPN structure is the product of risk factors:

$$RPN_i = F_i \cdot S_i \cdot T_i$$

Step 3: Why multiplication?

Because multiplication ensures:

- low value in one dimension lowers the total risk,
- high values in all three dimensions sharply increase the total,
- ranking becomes easy.

Step 4: If raw data are used instead of scores

If raw incident count, downtime hours, and severity weight are available, one may construct

$$RPN_i = f_i \cdot s_i \cdot \tau_i$$

where $f_i$is observed frequency, s_ia severity coefficient, and $\tau_i$time consumed.

6.1. Case Study A: Nuclear Plant Cooling System

A nuclear plant operator sought support for a complex, largely bespoke cooling system. Dependable 24/7 operations depended on

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the design quality, adequacy of staffing and scheduled competencies, comprehensive reports on ongoing activities, and a clear task escalation process in case of failures. Historical incident data for a critical remediation task in the cooling system provided the basis for quantifying incident management processes, mapping root causes to skill categories, and identifying competence gaps underlying incidents. Actual skill-matching capabilities were compared with the skill-moc matrix derived from quantified incident management processes and reported incidents over the preceding six years. Current and future staffing plans provided additional information for identifying training requirements, enabling workforce analytics to tackle immediate areas of concern while laying the groundwork for a more holistic long-term approach.

A Data Center operator strove to meet customer service requirements through an efficient incident management process for its power infrastructure supporting multiple data centres and customers. Analysis was performed for all incidents reported on four of the nine Data Center power infrastructure since inception. The NIST framework was adapted to the Data Center context and the outcomes reported for each of the five phases – Prevention, Identification, Containment, Eradication & Recovery, and Lessons Learned – both qualitatively and quantitatively. The effort culminated in displaying the overall effectiveness of incident management, creating awareness among involved stakeholders, and enabling continuous improvement through multiple improvements to people, process, technology and services within the Data Center incident management operations.

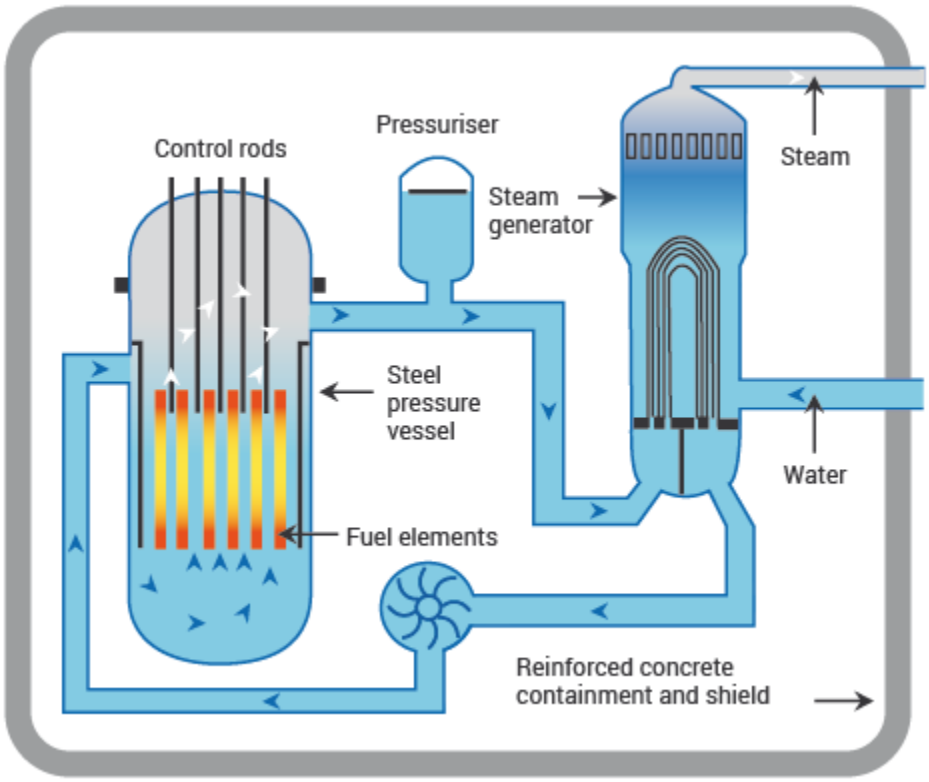

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Fig 6: Cooling Nuclear Power Plants

6.2. Case Study B: Data Center Power Infrastructure

Data Centers are most vulnerable to power outages. A Data Center operator planned to establish more than one Data Center in a country, with protected service continuity by diverse interconnections with adjacent Power Supply Companies. The normal power supply was ensured through multiple feeders and power supply rooms, while uninterruptible supply through power Houses. Here, the focus is on previewing outage reality with regard to power infrastructure through on-board performance indicators. With Vendor recommendations and management considerations, an aim for 99.982% uptime envision is made on a ten-year span life cycle. A primary review of 1,645 outage intervals through these supporting systems reveal that external interruptions overwhelm natural failure events with five times more intervals and seventeen times the sum outage time. The majority of external interruptions also fall into on-time response categories.

The detection and reporting of incidents were prompted by the nature of these supporting systems. The multistage and multilayer staff organization of an Indian Data Center took to Custodians' roles in P&M Monitoring. These were O&M Specialists or Administrators on how-to, with Non-Technical–Managed Service Provider Co-ordinators completing other contacts. However, the detail of automated monitoring features of all PLANT systems and the IEM login facilities for NETWORKING Infrastructure also complemented with Facility Management tools gave a high accuracy of Event Detection and Notification apart from their Vendor-expected fast-optimised Response Time for any Detectable Error Events.

7. Challenges and Risk Management

Effective implementation of workforce analytics in support of incident management processes in Power & Cooling (P&C) operations can face certain challenges and risks. These possibilities must be carefully considered and understood to assure successful outcomes; appropriate mitigations must then be evaluated and put in place as necessary. Two of the most prominent risk areas are data quality, accuracy, and privacy characteristics, and the degree of supportive engagement from stakeholders and associated change management processes.

Working with accurate, reliable, and relevant information is critically important. Poor data quality is a prime reason for failure in analytically enabled ventures. In the case of Workforce Analytics for Incident Management augmentations in P&C systems, relevant information resides in multiple sources, including area and corporate databases. Conducting a health check and quality score carding for each source, and putting error-capture and correction processes in place, forms a strong defence. Given the nature of Power and Cooling P&C incident records, Datenschutz regulations and other confidentiality concerns do place restrictions on the use of certain particulars, but anonymisation or aggregating of data, especially for reporting metrics, typically addresses these challenges.

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Method	Description	Key Metrics
Recovery Time Analysis (RTA)	Measures efficiency of incident recovery	Mean Recovery Time
Post-Incident Review (PIR)	Evaluates organizational and cultural factors	Culture score, feedback ratings
MTTR	Mean Time to Recover	Time duration
MTBF	Mean Time Between Failures	Reliability metric
Incident Frequency Analysis	Tracks occurrence rate	Number of incidents
Cost Analysis	Evaluates financial impact	Downtime cost

Table 3: Analytical Methods & Metrics Table

7.1. Data Quality and Privacy

It is crucial to prevent multiple individuals from being assigned the same task unless the incident during execution is unmanageable. As incident responses generate reams of uninterpreted data, ensuring its quality during both the recovery and post-incident review processes should thus be a top priority for any organization. Neglecting this factor will lead learners down the research-crunching rabbit-hole of producing advanced yet unfocused physics that bear scant relevance—installed equipment, changes to operational or environmental parameters, testing results, and design conditions need to be carefully catalogued. Failure to apply discernment during their interpretation leads to confused conclusions and wasted preparatory work. Data cleansing at the time of importing the information and thorough QA procedures throughout the research preparation processes are thus key enablers of success.

Incident management is by its very nature a sensitive activity. Facilities providers must treat all such data with the utmost care. All stakeholders possessing personal information about an incident responder should therefore give their approval prior to the use of that individual's information in analytics works. Should extenuating circumstances preclude the possibility of their consent, the safeguards outlined in the preceding subsection must be put in place. Moreover, the above combined with adequate

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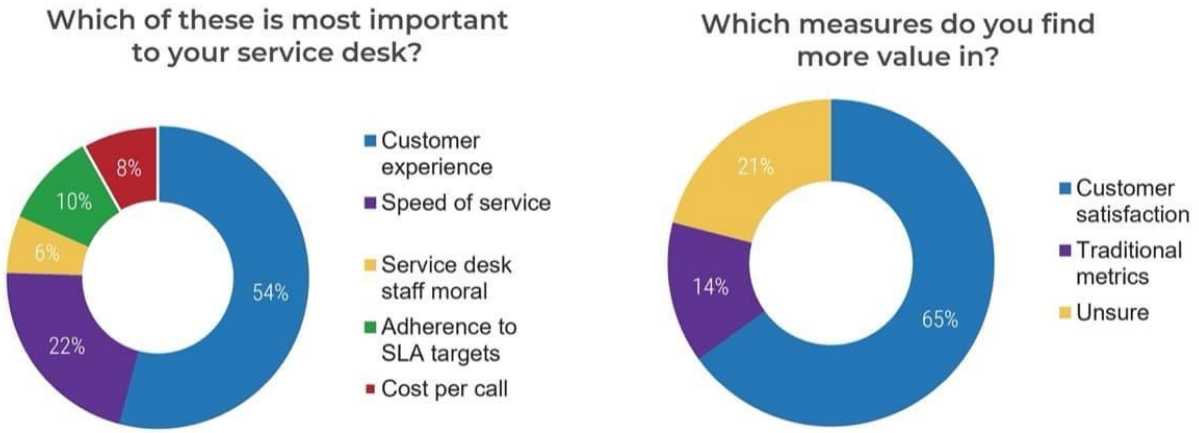
anonymization will enable a service provider to use incident data for training and the clarification of potentially misleading automation end results without resorting to data aggregation.



7.2. Change Management and Stakeholder Engagement

Planning and performing changes to incident management processes, tools, and data structures require an engagement program that clearly communicates the rationale and expected benefits of the changes to the workforce. Ongoing engagement of employees who perform or supervise incident-related activity is essential throughout the lifecycle of an initiative. Stakeholders should validate that the proposed improvements remain aligned with their requirements and areas of concern prior to project initiation. They should progressively validate and prioritize logical assumptions, architectural designs, and technical details that require their expert judgment in order to minimize the time, cost, and risk of rework. Validated change proposals and baseline analytics typically generate broad support required for change adoption.

Incident management functions in power and cooling operations at data centers and critical facilities are sometimes delegated to external or cross-functional teams that lack appropriate skills, knowledge, and real-time situational awareness. Function-specific metrics are commonly used to manage response performance, often leading to silo behavior that detracts from overall service quality. Analysis of response work through a dedicated lens aligned to the needs of the function being supported typically reveals opportunities to improve service quality, minimize resource demand, and enhance the worker experience.

8. Conclusion

Organizations in power and cooling operations must contend with the increasing complexity of their infrastructure while ensuring reliability, availability, safety, and environmental protection. Incident management processes remain key to achieving these goals

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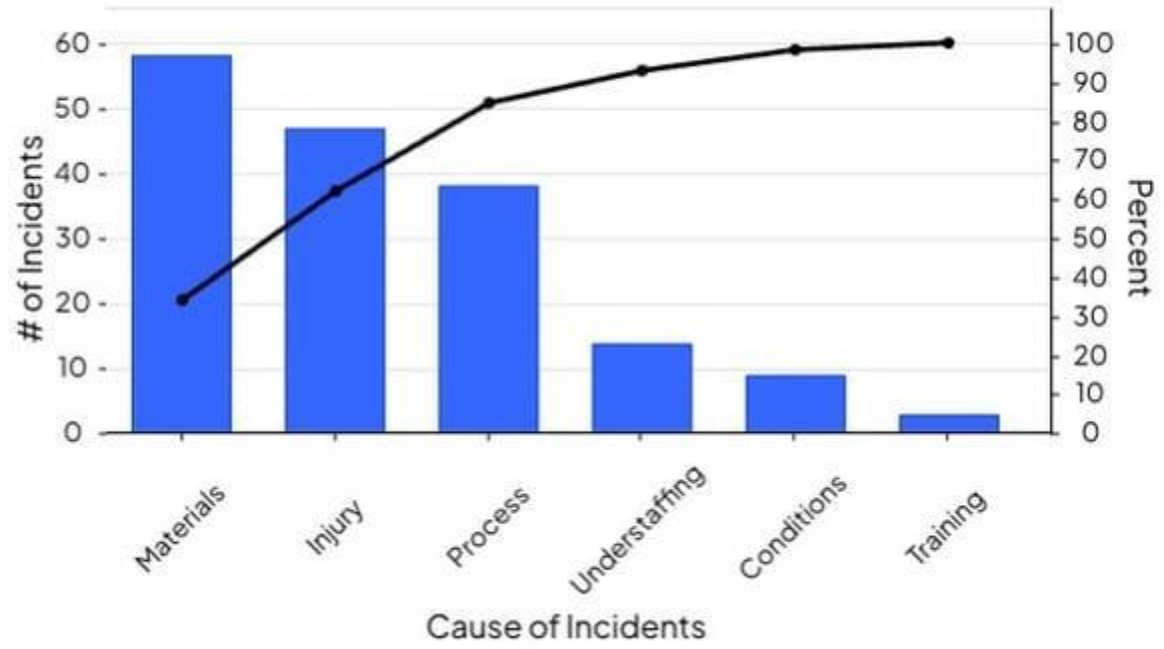
despite hundreds of years of cumulative experience and pioneering work in analysis and knowledge management. Sharing anecdotal reports on studies of incident-management knowledge through the lens of a human-chance factor provide a refreshing analytics perspective. Recent case studies leverage the full breadth of workforce analytics to enhance incident management in power and cooling systems.

Nuclear-generation cooling systems, for instance, require close coordination among multiple units and external organizations. The growing frequency of non-routine events of lesser severity has led to the recognition of the importance of analyzing incidents beyond cost recovery. A cold-plate system monitoring and control incident at a data center highlights the temptation to treat incidents as isolated occurrences rather than latent opportunities. Tools such as heat- and skill-matching matrices can help identify training needs associated with known weaknesses. Although continuous improvement is a business imperative, proper resourcing and scheduling of initiatives by an independent authority can ensure that such efforts maintain independence and offer clear value-adding recommendations.



8.1. Emerging Trends

The global political discourse addressing climate change's impact on the economy intends to inspire national support for the energy transition, enabling support from broader interest groups. The sector is currently experiencing a boom, leading to a temporary boom-bust profile for select submarkets, like the solar sector's dependency on Chinese supply chain. Nevertheless, the global progress towards achieving the net-zero goal by 2050 remains too slow. The projected balance between supply and demand can remain positive only if industry participants take the right action in a timely manner.

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As anticipated, the trend towards electrifying forms of transport is growing rapidly. Electric vehicle activity in China is surging buoyed by strong demand, innovative technologies, supportive government policies, and ambitious targets of local manufacturers. The rolling out of electrification presents a clear risk to coal sector demand while also being supportive of metals and battery chemicals en route to a low-carbon economy—further investment in low-carbon technology is now a critical regional enabler for longer-term success. In addition, increased demand for energy storage systems, especially batteries, should be driven in part by the need to support grid decarbonization, as seen in the solar and wind industries in China and broader APAC.

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