

Quantifying Asset Downtime in CCUS Value Chains: Impacts on Carbon Credit Generation and Strategies for Mitigation

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Abstract

Carbon Capture, Utilization, and Storage (CCUS) is becoming an important part of global efforts to reduce carbon emissions. It is especially relevant for industries where emissions are difficult to avoid through electrification or renewable energy alone. Most CCUS research has focused on capture technology, CO₂ transport, and long-term storage. Less attention has been given to how equipment downtime affects the performance of the full CCUS value chain.

In practice, the amount of CO₂ that can be transported and stored depends on the availability of capture units, compressors, pipelines, and injection facilities. If one of these assets is unavailable, the impact may extend to other parts of the system. This can reduce CO₂ throughput and storage volumes and may also affect the carbon credits associated with the project.

This study develops a deterministic, event-based hourly simulation that represents capture, compression, transport, injection, and storage as a capacity-constrained network. The numerical evaluation uses a transparent synthetic scenario dataset containing 8,760 hourly time steps per scenario for a 1.0 MtCO₂/year system, four system-uptime cases (99%, 97%, 95%, and 90%), five representative downtime events, and carbon prices of USD 30, 60, and 100/tCO₂. At each time step, the algorithm propagates asset availability through the network, identifies the limiting available capacity, integrates verified stored CO₂, and converts the difference from the planned baseline into credit and revenue exposure. For field deployment, the framework specifies an AI/ML pipeline using Isolation Forest for unlabelled sensor-anomaly screening and a gradient-boosted decision-tree classifier for predicting a failure within a defined 24-hour horizon.

The study also looks at ways to reduce the impact of downtime. These include predictive maintenance, digital monitoring, Industrial Internet of Things technologies, and digital twins. Scenario-based analysis is used to examine how better asset availability could help maintain storage capacity, improve system resilience, and reduce potential revenue losses. The paper also considers the reporting and carbon-accounting issues related to downtime as carbon markets develop.

By connecting asset reliability with CO₂ storage and carbon-credit performance, this study shows why equipment availability should be considered throughout the CCUS value chain. The proposed framework can help project teams understand the operational and financial effects of downtime and identify areas where maintenance and monitoring improvements may provide the greatest benefit.

Keywords

Asset Reliability, CCUS Downtime, Carbon Credit Loss, Digital Monitoring Systems, Predictive Maintenance.

INTRODUCTION

Carbon Capture, Utilization, and Storage (CCUS) can help reduce greenhouse gas emissions from industries that are difficult to fully decarbonize. Sectors such as cement, steel, refining, and power generation continue to consider CCUS as part of their long-term emission-reduction plans. It allows these industries to reduce emissions while continuing to use much of their existing infrastructure [1], [2].

CCUS projects are also becoming larger and more connected. Early projects often focused on individual demonstration facilities. Commercial projects may now include capture plants, compressors, pipelines, injection

facilities, and underground storage sites. These assets work together as one value chain [2], [3].

The performance of the full system depends on the availability of each part. A capture plant may operate efficiently, but the captured CO₂ cannot be stored if a compressor, pipeline, or injection well is unavailable. A disruption in one asset can therefore reduce throughput across the wider system. In many cases, the amount of CO₂ stored is limited by the asset with the lowest available capacity [3], [4].

This issue also affects the financial performance of a CCUS project. Carbon credits are generally linked to verified amounts of CO₂ that have been captured, transported, and permanently stored. If downtime reduces the amount of CO₂

reaching the storage site, the project may generate fewer credits. Lower asset availability can therefore affect storage targets, project revenue, and long-term commercial performance [2], [3].

The connection between asset availability and carbon credits is likely to become more important as carbon markets develop. Project owners and operators may need to provide clearer evidence of how much CO₂ was handled at each stage of the value chain. They may also need to explain production losses, interruptions, and differences between planned and actual storage volumes.

Most CCUS research has focused on capture efficiency, transport safety, reservoir behaviour, and storage integrity [3], [4], [5]. This work has improved the technical understanding of each stage. However, the different stages are often studied separately. Fewer studies have examined how downtime in one asset affects connected assets or how these events influence total storage volumes and carbon-credit outcomes.

Other industries use predictive maintenance, condition monitoring, digital twins, and data-based diagnostic tools to improve equipment availability [6], [7], [8]. These methods can identify signs of equipment failure before a breakdown occurs. Maintenance can then be planned before the problem causes a major interruption.

These methods are widely used in manufacturing and process industries, but their use across an integrated CCUS value chain is still developing. Their value is also often measured in terms of equipment performance or reduced maintenance cost. Less attention is given to how they may help maintain CO₂ throughput, preserve storage volumes, and protect carbon-credit revenue.

During project planning, downtime is commonly represented as an annual availability percentage. This provides a useful estimate, but it may not show how a real disruption moves through a connected system. For example, a compressor outage may force a capture plant to reduce output. It may also change pipeline conditions, interrupt injection schedules, and reduce the amount of CO₂ verified as permanently stored. These effects can occur even when the other assets remain available.

A system-level approach is therefore needed to understand the full impact of downtime. Such an approach should consider the capacity and availability of each asset, the connections between assets, and the way a constraint in one part affects the rest of the value chain.

This paper makes three specific contributions (1) an hourly deterministic algorithm that propagates asset-level downtime through a connected CCUS network, (2) a reproducible scenario dataset and calculation chain linking downtime to verified storage, credits, and revenue and (3) a field-deployment AI/ML design for converting sensor and

maintenance data into early-warning probabilities. The first two contributions are evaluated numerically in this paper; the AI/ML design is specified but not trained or benchmarked because labelled field data were not available.

The study further considers how predictive maintenance, digital twins, real-time monitoring, and operational planning could reduce downtime and improve system resilience. By linking equipment reliability with carbon accounting, the work provides a practical way to assess how digital technologies may support both the environmental goals and commercial performance of CCUS projects.

LITERATURE SURVEY

Development of CCUS Technologies

Over the past two decades, most CCUS research has focused on improving each part of the value chain. This includes developing better capture technologies, comparing methods for transporting CO₂, improving the understanding of storage reservoirs, and ensuring that stored CO₂ remains underground over the long term [1], [2], [3], [4]. This work has helped establish CCUS as a practical option for reducing emissions from large industrial sources.

As CCUS projects moved from laboratory studies to commercial demonstrations, researchers began to study capture, transport, and storage as parts of the same project. Techno-economic studies were used to estimate project costs, compare infrastructure options, and support investment decisions [5], [6].

However, many of these studies represented availability using a single average value for the full system. This approach is useful for early project planning, but it may not show the effect of actual operating events. Short outages, equipment restart times, reduced-capacity operation, and failures affecting several connected assets often receive less attention.

Carbon Accounting and Carbon Credit Generation

The growth of carbon markets has added a financial element to CCUS performance. Carbon-accounting methods define how captured and permanently stored CO₂ is measured and verified. The verified quantity may then be used for regulatory compliance or to generate carbon credits in voluntary markets [3].

Most carbon-accounting methods focus on measurement accuracy, monitoring requirements, storage permanence, and the risk of leakage. Equipment downtime is usually considered only through its effect on annual storage volumes. Less attention has been given to how a specific outage affects the amount of CO₂ that can be verified during a reporting period.

For example, a compressor shutdown may reduce the

amount of CO₂ delivered to the injection site. Even if capture operations return to normal after a short period, the lost storage volume may not always be recovered. This can reduce the number of carbon credits generated during that reporting period.

As the value of carbon credits changes and reporting rules become more detailed, the financial effect of downtime may become more important. Even a short interruption could affect storage targets and project revenue, particularly in projects operating close to their available transport or injection capacity.

Downtime and Operational Reliability

Equipment reliability is an important part of operations in industries such as oil and gas, power generation, and process manufacturing. These industries use planned maintenance, equipment redundancy, spare capacity, and condition monitoring to reduce production losses and avoid unexpected shutdowns [7].

Downtime has received less attention as a system-level measure in CCUS studies. Equipment availability is often calculated separately for capture plants, compressors, pipelines, and injection facilities. In practice, however, these assets are connected and must operate together.

A capture plant may remain available while a compressor is offline, but the captured CO₂ may not be transported unless temporary storage or another transport route is available. Similarly, an unavailable injection well may limit pipeline flow and require upstream capture facilities to reduce production.

A failure in one location can therefore restrict throughput across the wider value chain. The effect of the failure may be greater than its duration or local production loss would suggest. The connection between individual equipment reliability and overall CCUS performance has not yet been studied in enough detail.

Digital Technologies for Reducing Downtime

Digital technologies have changed the way industrial equipment is monitored and maintained. Continuous monitoring, predictive analytics, Industrial Internet of Things devices, and digital twins can help operators identify signs of equipment degradation before a failure occurs [7], [8].

Early detection gives maintenance teams more time to plan repairs and arrange the required people, tools, and spare parts. This may reduce unplanned shutdowns and shorten the time needed to return equipment to service.

These technologies are already used in manufacturing, oil and gas, and power generation. Reported applications include equipment-condition monitoring, fault detection, maintenance planning, and performance analysis.

Within CCUS, digital technologies have mainly been used

to monitor specific equipment, study reservoir behaviour, or support geological modelling. Their use for managing the availability of the full CCUS value chain is still limited.

As CCUS projects grow and connect multiple facilities, digital monitoring needs to extend beyond individual assets. Information from capture plants, compressors, pipelines, injection wells, and storage sites should be reviewed together. This could help operators identify how a developing problem may affect the wider system and decide where early action would provide the greatest benefit.

Dependencies across the CCUS System

A commercial CCUS project contains assets that depend on one another. The capture plant supplies CO₂ to the compressor, the compressor feeds the transport network, and the pipeline delivers CO₂ to the injection facilities. The injection facilities must then operate within the limits of the storage reservoir.

The capacity and availability of each asset can affect downstream and upstream operations. If pipeline capacity is reduced, a capture plant may need to lower its output. If an injection well becomes unavailable, the pipeline may not be able to accept the planned flow. The effect may be larger in hub-and-cluster projects, where several capture facilities share the same transport and storage infrastructure.

Recent infrastructure studies recognize that transport bottlenecks and storage limits can restrict upstream capture [2], [3], [4], [5], [6]. However, many studies do not calculate how downtime in one asset moves through the complete value chain. They also provide limited information about how the resulting loss of storage volume affects carbon-credit generation.

Understanding these effects requires a system-level approach. The analysis must consider not only the availability of each asset but also its capacity, position in the network, and relationship with other assets.

Research Gap

Existing studies provide a strong understanding of CCUS technologies, infrastructure planning, carbon accounting, equipment reliability, and industrial digitalization. However, these topics are often studied separately.

There is limited guidance on how downtime should be assessed across an interconnected CCUS system. In particular, more work is needed to understand how a temporary failure in one asset affects system throughput, verified storage volumes, and potential carbon-credit value.

Predictive maintenance and digital-twin technologies have shown value in other industries. However, their ability to maintain CO₂ throughput and protect carbon-credit value across a complete CCUS system has not been studied in the same depth.

This study addresses these gaps by presenting a framework that connects asset availability, CO₂ throughput, storage volume, and potential carbon-credit generation. Downtime is not treated only as a maintenance measure for individual equipment. Instead, the framework examines how an interruption affects connected assets across the value chain.

The study also considers how digital monitoring, predictive maintenance, and digital twins could reduce the frequency or duration of these interruptions. This provides a way to assess both the operational and financial value of improving asset reliability in commercial CCUS projects.

METHODOLOGY AND SOLUTION

This study presents a method for estimating how equipment downtime affects an entire CCUS value chain. It also converts the resulting loss in CO₂ storage into potential carbon-credit and revenue impacts.

The method does not assess each asset separately. It considers how capture units, compressors, transport systems, and injection facilities depend on one another. A problem in one part of the system may reduce the throughput of several connected assets.

The framework has a modular design. It can be used for a simple project with one capture plant and one storage site or for a larger hub-and-cluster project with several emitters sharing transport and storage infrastructure.

System Architecture

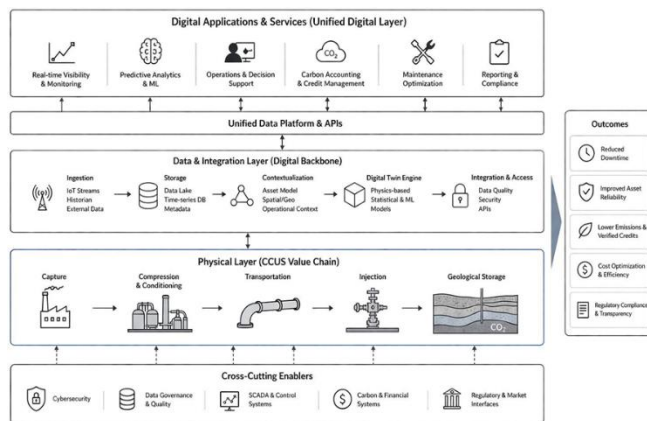


Figure 1: Integrated CCUS downtime quantification and mitigation architecture

Figure 1 shows the system architecture used to assess and reduce the effects of downtime. The architecture contains two connected layers: the physical CCUS system and the digital monitoring environment.

The physical layer represents the main parts of the CCUS value chain:

- Capture facilities
- Compression and dehydration units
- Transport systems

- Injection facilities and wells
- Geological storage sites

These assets operate as a connected process. CO₂ captured at an industrial facility must be conditioned, transported, injected, and stored. A reduction in capacity or availability at any stage may limit the amount of CO₂ handled by the rest of the system.

The digital layer combines live operating data, asset history, engineering information, and analytical models. Data are collected from SCADA systems, field sensors, process historians, and other operational sources. The data are organized within a common model so that equipment condition can be viewed in the context of the full value chain.

A digital twin is used to test different operating scenarios. These may include:

- Planned maintenance
- Partial loss of equipment capacity
- Unexpected equipment failure
- Utility or power interruption
- Equipment restarts and recovery
- Changes in transport or injection capacity

The scenarios allow project teams to estimate CO₂ throughput losses and compare maintenance or recovery options without interrupting live operations.

The framework also supports predictive maintenance. Historical operating data are combined with current sensor measurements to identify changes in equipment condition. The aim is to detect developing problems early and schedule maintenance at a time that causes the least disruption to the overall system.

Operational performance is then linked with carbon accounting. The amount of CO₂ eligible for credit is calculated using the verified quantity that passes through the required stages and is permanently stored. This provides a direct link between equipment availability, storage performance, carbon reporting, and potential project revenue.

Data QA/QC, Validation, and Uncertainty

Before calculation, the data pipeline performs schema and unit checks, duplicate removal, UTC timestamp alignment, sensor-range and rate-of-change checks, asset-ID reconciliation, and mass-balance checks between captured, transported, injected, and stored quantities. Missing or suspect measurements retain an explicit quality flag. They are not silently converted to zero, and outage intervals are not imputed across. MRV values are reconciled to the approved reporting ledger, while model inputs, versions, thresholds, and scenario assumptions are stored with an audit identifier. These controls distinguish equipment unavailability from missing data and support independent recalculation.

Arithmetic validation uses closed-form cases, including a

fully available system, a complete single-asset outage, and a partial-capacity restriction. Network implementations should additionally be tested for conservation of mass, capacity limits, parallel-route allocation, and restart constraints. Uncertainty is evaluated by varying uptime, outage duration, unavailable-capacity fraction, recovery fraction, MRV eligibility factor, and carbon price. Field deployment requires back-testing against unseen time periods and prospective monitoring for drift and false alarms.

System Boundary and Value Chain Definition

For this study, the CCUS value chain covers the assets used to capture, condition, transport, inject, and permanently store CO₂. The system boundary includes:

1. Capture units at power plants or industrial facilities
2. Compression and dehydration systems used to meet transport requirements
3. Transport infrastructure, such as pipelines or shipping systems
4. Injection facilities and wells connected to geological storage sites
5. Measurement and monitoring systems used to verify stored CO₂

Each asset is assigned an operating capacity, availability profile, and expected recovery time. An asset may be fully available, completely unavailable, or operating at reduced capacity.

The assets depend on one another. For example, an unavailable compressor may reduce the flow from the capture plant even if the capture unit is operating normally. Similarly, limited injection capacity may restrict pipeline flow and cause upstream capture facilities to reduce output.

This representation allows the framework to model how downtime moves through the CCUS value chain.

Downtime Characterization and Classification

Downtime is divided into two categories: planned and unplanned.

Planned downtime includes:

- Scheduled maintenance
- Routine inspections
- Equipment testing
- Regulatory shutdowns
- Planned system upgrades

Unplanned downtime includes:

- Equipment failures
- Process disturbances
- Power or utility interruptions
- Instrument and control-system failures
- Unexpected transport or injection restrictions

Each downtime event is represented by its start time, duration, and severity. Severity describes whether the asset is

fully unavailable or continues to operate at reduced capacity.

This event-based approach gives more detail than using only one annual availability value. It captures short outages, partial loss of capacity, and the time required to restart an asset after repairs.

The average availability of asset i , represented by A_i , is calculated as:

$$A_i = 1 - (Total\ Downtime_i / Total\ Time) \quad (1)$$

This equation provides an overall availability value for the selected period. For the scenario analysis, however, availability is also represented as a time-dependent value, $A_i(t)$. This allows the model to show when an event occurred and how the operational condition changed during the event.

A value of 1 means that the asset is fully available. A value of 0 means that it is unavailable. Values between 0 and 1 represent reduced-capacity operation.

CO₂ Throughput Modelling

The amount of CO₂ that can move through the value chain depends on the available capacity of all connected assets. A fully operating capture plant cannot continue at its planned rate if there is not enough compression, transport, or injection capacity.

For a simple value chain in which all assets have the same normalized design capacity, the available CO₂ throughput at time t can be approximated as:

$$C(t) = C_n \times \min\{A_1(t), A_2(t), \dots, A_n(t)\} \quad (2)$$

where:

- $C(t)$ is the available system throughput at time t ;
- C_n is the planned CO₂ throughput under normal operation; and
- $A_i(t)$ is the available fraction of capacity for asset i at time t .

The minimum function represents the limiting asset in a simple series-based CCUS chain. For example, if all assets are fully available except for a compressor operating at 60% capacity, the system throughput is limited to 60% unless temporary storage, spare equipment, or another operating route is available.

For projects with several capture sources, parallel compressors, multiple pipelines, buffer storage, or several injection wells, a network-flow model should be used instead of the simple minimum function. Such a model can account for the rated capacity of each asset, alternative flow paths, temporary storage, and operating constraints.

The total CO₂ handled during an accounting period T is calculated by integrating the system throughput over time:

$$Q_{\text{handled}} = \int_0^T C(t) dt \quad (3)$$

The quantity eligible for carbon credits should be based on verified stored CO₂ rather than captured CO₂ alone. Measurement losses, venting, transport losses, injection restrictions, and verification rules may therefore need to be included when converting system throughput into credited storage volume.

Carbon Credit and Revenue Impact

Definition of CO₂ Reduction and Carbon-Credit Eligibility

Two baselines are kept separate. The operational loss assessed in this paper is the difference between planned verified storage and actual verified storage during the accounting period. The climate benefit of the CCUS project is the metered quantity permanently stored relative to the applicable no-CCUS emissions baseline, after deducting transport losses, venting or leakage, and any direct or indirect project emissions required by the governing methodology. Captured CO₂ alone is therefore not counted as emissions reduction or as a credit. One credit per tCO₂ is used only as a transparent scenario assumption; actual issuance remains subject to the selected registry methodology, additionality, permanence, leakage, ownership, and third-party verification requirements.

The loss of CO₂ throughput is calculated by comparing planned operation with actual operation during the accounting period.

For a constant planned throughput, the operational throughput loss is:

$$L = \int_0^T [C_n - C(t)] dt \quad (4)$$

where L represents the amount of planned CO₂ throughput lost because of downtime or reduced-capacity operation.

This value does not always equal the final loss of carbon credits. Some lost throughput may be recovered later if spare capture, transport, or injection capacity is available. The final credit impact should therefore be calculated from the difference between planned and verified storage volumes:

$$L_{\text{credit}} = Q_{\text{verified, planned}} - Q_{\text{verified, actual}} \quad (5)$$

If one carbon credit represents one verified unit of stored CO₂ under the selected accounting method, the potential revenue impact can be estimated as:

$$R = L_{\text{credit}} \times P \quad (6)$$

where:

- R is the potential revenue loss;
- L_{credit} is the reduction in verified and eligible stored CO₂; and
- P is the applicable carbon price per unit of CO₂.

Several carbon-price scenarios can be tested because the future price may be uncertain. For example, the same outage can be assessed under low, base, and high price cases. This

shows how the financial effect changes with market conditions.

The calculation should also account for any relevant verification costs, contractual penalties, replacement-credit costs, or limits on credit eligibility where these apply.

Modelling the Spread of Downtime

A main purpose of the framework is to show how a local disruption can affect the wider CCUS system. Different scenarios are created by introducing downtime or reduced capacity at selected assets.

For each scenario, the model records:

1. The asset where the event begins
2. The time and duration of the event
3. The reduction in available capacity
4. The effect on connected upstream and downstream assets
5. The time required for the system to recover
6. The resulting change in verified storage volume
7. The potential effect on carbon-credit revenue

For example, a compressor outage may force a capture plant to reduce its throughput, even when the capture equipment remains available. An injection restriction may reduce pipeline flow and eventually limit several upstream capture facilities. In a shared transport network, the same outage may affect more than one emitter.

The framework can also consider whether the system has spare capacity or alternative operating options. These may include standby compressors, parallel pipelines, additional injection wells, temporary CO₂ storage, or the ability to increase throughput after the affected asset returns to service.

Including these options provides a more realistic estimate of the final storage loss than assuming that all throughput lost during an outage is permanently unrecoverable.

Digital Decision Support

The digital monitoring environment combines current operating measurements with equipment history and maintenance information. This helps operators identify abnormal behaviour before an equipment failure becomes critical.

The digital twin can be used to compare maintenance and recovery options. For example, operators can assess:

- Whether maintenance should be performed immediately or delayed
- Whether a standby asset should be placed in service
- Whether CO₂ flow should be redirected
- Whether another injection well can accept additional flow
- Whether lost throughput can be recovered later
- Which maintenance action protects the greatest

storage volume

Each option can be compared using practical measures such as expected downtime, CO₂ throughput loss, recovery time, maintenance cost, and potential carbon-credit impact.

The framework supports engineering decisions, but it does not replace operator judgement or established safety procedures. Any recommended action must remain within equipment limits, operating procedures, regulatory requirements, and storage-site constraints.

Carbon-Credit Assurance

The framework records downtime events together with operational and storage data. This creates a traceable record of when an event occurred, which assets were affected, how throughput changed, and how much CO₂ was ultimately verified as stored.

The record may include:

- Event start and end times
- Affected assets
- Cause of downtime
- Planned or unplanned classification
- Available capacity during the event
- Captured, transported, injected, and verified volumes
- Data-quality status
- Recovery actions
- Supporting measurement records

Connecting these records with the carbon-accounting process improves transparency. It also helps explain differences between planned storage targets and actual verified storage volumes.

By linking asset availability with verified storage, the framework supports carbon-credit calculations based on actual project performance rather than capture estimates alone.

Practical Methodology Workflow

The complete assessment follows these steps:

1. Define the CCUS system boundary and asset network.
2. Record the capacity and operating limits of each asset.
3. Collect historical downtime and maintenance information.
4. Define planned and unplanned downtime scenarios.
5. Represent full and partial availability as time-dependent values.
6. Calculate system throughput for each time step.
7. Model upstream and downstream effects across connected assets.
8. Calculate actual injected and verified storage volumes.
9. Compare actual storage with the planned baseline.
10. Convert eligible storage losses into potential carbon-

credit impacts.

11. Test maintenance, redundancy, and recovery options.
12. Compare the operational and financial results of each option.

This workflow provides a consistent way to study the effect of downtime across a connected CCUS project. It also helps identify which assets have the greatest influence on storage performance and where maintenance or additional capacity may provide the greatest practical value.

AI/ML Methodology for Field Deployment

The AI/ML component is a two-stage early-warning pipeline. Stage 1 uses Isolation Forest, an unsupervised anomaly-detection algorithm, to screen multivariate sensor windows when reliable failure labels are sparse. Stage 2 uses a gradient-boosted decision-tree binary classifier to estimate whether a defined functional failure will occur within the next 24 hours. Candidate predictors are 1-hour and 24-hour rolling mean, standard deviation, slope, and rate of change for pressure, temperature, flow, vibration, and power, together with operating mode, starts/stops, alarm counts, time since maintenance, and equipment age. Failure labels are derived only from approved maintenance work orders and event logs.

To prevent information leakage, records must be split chronologically by event before feature scaling or window construction. The earliest 70% for training, the next 15% for validation and threshold selection, and the latest 15% for testing. Class weighting is used for rare failures. Reported field-model metrics must include precision, recall, F1 score, area under the precision-recall curve, false alarms per operating month, probability calibration, and warning lead time. The selected alert threshold is based on the cost of an unnecessary intervention versus the expected verified-storage and revenue loss from a missed failure.

The model output is a failure probability and anomaly score, not an automatic control command. These outputs create candidate downtime scenarios for Algorithm 1, which compares immediate maintenance, delayed maintenance, standby equipment, and rerouting. An operator approves any action under existing safety and operating procedures. No model was trained for the present paper, and the deterministic results in the Results section must not be interpreted as ML accuracy or field performance.

Model Assumptions and Limitations

The numerical evaluation assumes constant planned flow, one-hour time steps, no buffer storage, no alternative route, no post-outage recovery of lost volume, and one eligible credit per verified tCO₂. It excludes capture-energy penalties, lifecycle emissions, leakage, taxes, discounting, contractual interactions, and dynamic reservoir constraints. The data are synthetic and representative rather than site-specific, and the

AI/ML workflow has not been trained or validated on field data. Consequently, the results demonstrate calculation logic and sensitivity. Project decisions require site-specific

topology, operating limits, MRV rules, carbon contracts, and prospective validation.

RESULTS

Table 1: Representative scenario dataset used in the numerical evaluation

ID	Affected Asset	Duration	Available fraction	Recovery Assumption	Storage Loss (tCO ₂)
U99	System	87.6 h equivalent	0 during equivalent outage	No recovery	10,000
U97	System	262.8 h equivalent	0 during equivalent outage	No recovery	30,000
U95	System	438.0 h equivalent	0 during equivalent outage	No recovery	50,000
U90	System	876.0 h equivalent	0 during equivalent outage	No recovery	100,000
E1	Capture unit	12 h	0.00	No recovery	1,370
E2	Compressor	24 h	0.00	No recovery	2,740
E3	Pipeline	48 h	0.50	No recovery	2,740
E4	Injection	72 h	0.60	No recovery	3,288
E5	Planned maintenance	120 h	0.00	No recovery	13,699

The deterministic algorithm was evaluated with the synthetic dataset in Table 1. A representative 1.0 MtCO₂/year CCUS value chain, 8,760 one-hour records per scenario, and a nominal constant rate of 114.16 tCO₂/h. One carbon credit per verified stored tonne and no recovery of outage losses were assumed. These assumptions make the reported values auditable and define the boundary within which they should be interpreted.

The evaluation isolates three causal drivers namely outage duration, unavailable-capacity fraction, and the position of the constrained asset in the network. Storage loss is first calculated physically; carbon price is applied only afterward, so price changes revenue exposure but not the quantity of CO₂ lost.

Effect of System Uptime

The first analysis examined how system uptime affects annual CO₂ storage and carbon-credit generation.

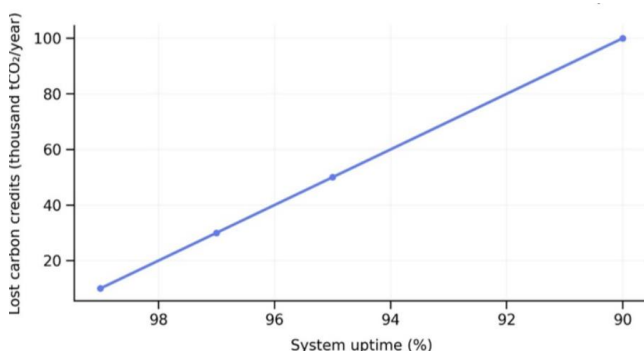


Figure 1: Annual carbon-credit loss at different CCUS system uptime levels.

As shown in Figure 2, the constant-flow baseline gives storage loss = 1,000,000 × (1 – uptime). The resulting annual losses are 10,000, 30,000, 50,000, and 100,000 tCO₂ at 99%, 97%, 95%, and 90% uptime, respectively. Under the assumed

one-credit-per-tonne method, these storage losses result in the same number of carbon credits being lost. The analysis assumes constant throughput and no recovery of lost volumes. The result shows that system availability directly affects both storage performance and potential carbon-credit revenue.

The result should therefore be used as a baseline showing the direct effect of system uptime. Later scenarios can build on this baseline by introducing asset-specific failures, partial capacity, redundancy, recovery time, and carbon-price variations.

Revenue Exposure Under Carbon Price Scenarios

The financial impact of downtime was estimated using carbon prices of USD 30, USD 60, and USD 100 per tCO₂.

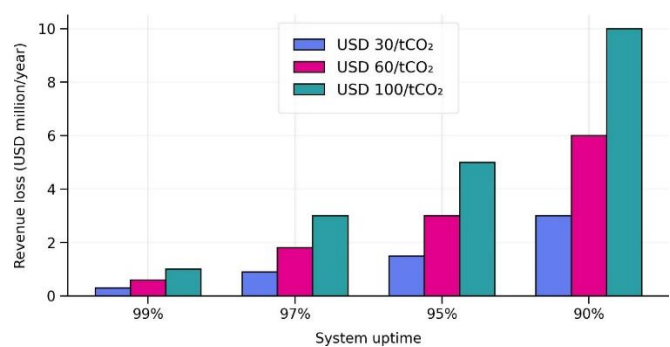


Figure 2: Estimated annual revenue loss under different system uptime and carbon-price scenarios.

Figure 3 applies revenue exposure = storage loss × carbon price after the physical calculation. At 95% uptime, 50,000 lost tCO₂ gives USD 1.5 million, USD 3.0 million, and USD 5.0 million at USD 30, 60, and 100/tCO₂, respectively. At 90% uptime, 100,000 lost tCO₂ gives USD 3-10 million. Thus, carbon price does not alter operational loss in this model. It scales the financial consequence and can change

which maintenance intervention is economically preferred.

Impact of Representative Downtime Events

The next analysis compared planned outages, equipment trips, and partial capacity reductions across the CCUS value chain.

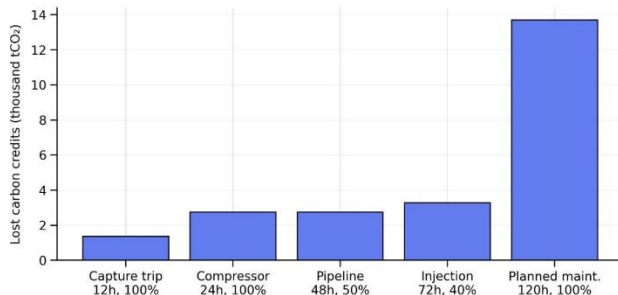


Figure 3: Carbon credit loss from representative downtime events

Figure 4 confirms that duration and severity combine multiplicatively. At 114.16 tCO₂/h, a 12-hour complete capture trip loses approximately 1,370 tCO₂, a 24-hour complete compressor outage loses 2,740 tCO₂, and a 48-hour pipeline restriction with 50% unavailable capacity also loses 2,740 tCO₂. A 72-hour injection restriction with 40% unavailable capacity loses 3,288 tCO₂, while 120 hours of complete planned maintenance loses 13,699 tCO₂. Equal losses from the compressor and pipeline cases show why ranking events by duration alone is misleading; the unavailable-capacity fraction and network bottleneck must also be included.

Benefits of Digital Mitigation Strategies

The final scenario tests the value of an assumed availability improvement from 94% to 97%. In the representative 1.0 MtCO₂/year project, increasing availability from 94% to 97% would add approximately 30,000 tCO₂ to annual verified storage. Under the assumed one-credit-per-tonne method, this would also preserve 30,000 carbon credits. The estimated annual value ranges from USD 0.90 million at USD 30/tCO₂ to USD 3.00 million at USD 100/tCO₂. These results show the potential business value of digital mitigation strategies, provided that the three-percentage-point improvement can be achieved in practice. The contribution of each strategy would need to be confirmed using field data.

Table 2: Potential economic value of improved system availability

Availability improvement	Additional stored CO ₂	Value at USD 30/tCO ₂	Value at USD 60/tCO ₂	Value at USD 100/tCO ₂
94% to 97%	30,000 tCO ₂ /year	USD 0.90 million/y	USD 1.80 million/y	USD 3.00 million/y

		ear	ear	ear
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Discussion of Results

The results support three conclusions within the stated assumptions. First, a series CCUS chain inherits the capacity of its limiting asset, so local downtime can create system-wide storage loss. Second, outage duration alone is insufficient, a long partial restriction can equal a shorter complete outage. Third, financial exposure is the product of a separately calculated physical loss and the applicable price. Keeping these stages separate prevents market assumptions from obscuring engineering performance.

Digital monitoring and the specified AI/ML pipeline could reduce risk by providing earlier evidence of degradation. Isolation Forest is appropriate for initial anomaly screening with sparse labels, while gradient-boosted decision trees provide a supervised failure probability and feature-level explanations when quality-assured failure labels become available. Their value must be demonstrated on chronologically held-out field data and then through prospective monitoring of warning lead time, false alarms, avoided downtime, and preserved verified storage.

For decision-making, system uptime should be reported with storage loss, MRV data quality, and uncertainty rather than as a standalone average. The transparent calculation chain and QA/QC controls allow an operator or verifier to trace a reported credit impact to the responsible event, meter records, assumptions, and model version.

CONCLUSION

This study provides a deterministic method for propagating asset downtime through a connected CCUS value chain and converting the resulting verified-storage shortfall into carbon-credit and revenue exposure. A fully specified synthetic dataset makes the scenario calculations reproducible. For a 1.0 MtCO₂/year baseline, annual storage loss ranges from 10,000 tCO₂ at 99% uptime to 100,000 tCO₂ at 90% uptime. At 95% uptime, the tested carbon prices produce USD 1.5-5.0 million/year of gross revenue exposure.

The event cases explain the mechanism behind these totals. A 24-hour complete compressor outage and a 48-hour pipeline restriction with 50% unavailable capacity each lose about 2,740 tCO₂. The comparison demonstrates that duration, severity, recovery, and network position must be assessed together. CO₂ reduction and credit calculations are based on eligible verified permanent storage, with applicable project emissions and losses deducted, rather than on captured CO₂ alone.

For field deployment, the paper specifies Isolation Forest anomaly screening and a gradient-boosted failure classifier integrated with the deterministic scenario algorithm, along with chronological validation and data QA/QC requirements.

Because no labelled field dataset was available, no ML accuracy or realized availability improvement is claimed. Future work should validate the framework through real CCUS deployments and include actual equipment, maintenance, storage, and carbon-market data.

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