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Role of Process Management in Digital Forensics for Windows-Based Environment

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Abstract

Process management in Windows plays a critical role in digital forensic investigations. Active and historical process data often provide evidence of malicious activity, unauthorized access, or abnormal system behavior. Unlike static artifacts such as event logs, process-level information offers real-time insight into what is running, how it interacts with the system, and how malicious actors attempt to disguise their activities. This paper explores the role of process management in Windows forensic analysis, presenting a structured methodology for capturing, storing, and analyzing process-related evidence. We discuss the classification of process artifacts, design an XML-based forensic storage model, demonstrate implementation strategies, compare with other evidence storage structures, and highlight real-world forensic use cases.

Keywords

Digital Forensics, Windows Processes, Process Management, Malware Detection, Evidence Preservation, Memory Forensics, Incident Response, XML Storage, Process Tree Analysis, Cybersecurity.

1. Introduction

In Windows systems, everything that runs on the machine — applications, services, and background tasks — is represented by a process. A process is the basic unit of execution: it has a unique identifier (PID), a command line, an owner (user or system account), loaded libraries, threads, and various runtime properties. For forensic investigators, process information is especially valuable because it shows *what was actually running* on the system at a given time, and how pieces of software interacted with the operating system and with each other [1][2].

Process-level evidence gives investigators a direct view of activity that is otherwise easy to hide. Attackers often run malicious code inside or alongside normal programs to avoid detection: they may spawn hidden child processes, inject code into legitimate processes, or use legitimate system tools (like PowerShell) to execute harmful commands. These behaviors are difficult to prove using only disk files or static logs, because malicious code can live only in memory or can reuse normal program names. Capturing process data helps reveal these hidden activities and shows the relationships between parent and child processes that often indicate suspicious behavior [3][4].

A key challenge is that process information is *volatile* — it exists in memory and in runtime tables, and it disappears when the machine is turned off or restarted [5]. That is why live acquisition and careful recording of process data are essential in incident response. Tools and methods for capturing processes include built-in Windows interfaces (WMI, Event Tracing for Windows), command-line tools (Tasklist, Get-Process), and specialized utilities such as

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the Sysinternals suite and memory acquisition tools like WinPMEM and Volatility [6][7]. Each method has trade-offs: some provide deep details but risk altering system state, while others are lower impact but capture less information.

For forensic work to be useful in investigations and in court, the way we collect and store process records must be consistent and auditable [8]. Structured formats make it easier to validate, search, and cross-reference process records with other sources — for example, with event logs, registry entries, or memory dumps. Storing process data in a schema-based format (such as XML with an accompanying XSD) supports automated parsing, schema validation, and signature-based integrity checks, which help preserve the chain of custody and make analysis reproducible [9][10].

To make analysis practical, we break process-related records into a few manageable categories that investigators commonly use:

- **Q1 — Running Processes:** current active processes and their basic fields (PID, name, owner, start time).
- **Q2 — Parent–Child Relationships:** which process created or spawned another. Unusual parent-child pairs (for example, a user process spawning cmd.exe or powershell.exe) can be a red flag.
- **Q3 — Loaded Modules and DLLs:** libraries and modules attached to a process. Malware often injects or loads unexpected modules, so listing these helps spot tampering.
- **Q4 — Thread Information:** threads and their states inside a process. Thread counts, unusual thread stacks, or threads created in rapid succession may indicate malicious behavior.
- **Q5 — Process Metadata:** command-line arguments, file paths, digital hashes of executables, privilege tokens, open handles, and network connections.

Putting these categories together gives a fuller picture than any single source alone. For instance, a suspicious command line (Q5) together with an odd parent (Q2) and a nonstandard loaded DLL (Q3) is much stronger evidence than any one of those items by itself. Cross-checking process snapshots with memory analysis, Windows event logs, and file-system records reduces false positives and improves confidence in findings [11][12].

Below is a compact XML example showing how process data can be recorded in a structured way. This kind of representation helps analysts run reproducible queries (XPath), validate fields (XSD), and sign stored records to guarantee integrity:

XML Structure to archive process data.

```
<ProcessData>
 <RunningProcesses id="Q1">
  <Process>
   <PID>4560</PID>
   <Name>chrome.exe</Name>
   <StartTime>2023-07-10T14:32:00</StartTime>
   <User>Premal</User>
  </Process>
 </RunningProcesses>

 <ParentChild id="Q2">
  <Relation>
   <ParentPID>4560</ParentPID>
   <ChildPID>4788</ChildPID>
   <ChildName>powershell.exe</ChildName>
  </Relation>
 </ParentChild>

 <Modules id="Q3">
```

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```
  <Module>
    <PID>4788</PID>
    <DLL>kernel32.dll</DLL>
    <Path>C:\\Windows\\System32\\kernel32.dll</Path>
  </Module>
 </Modules>

 <Threads id="Q4">
  <Thread>
    <PID>4788</PID>
    <TID>1234</TID>
    <State>Running</State>
  </Thread>
 </Threads>

 <Metadata id="Q5">
  <Process>
    <PID>4788</PID>
    <CommandLine>\"powershell.exe -nop -w hidden\"</CommandLine>
    <Hash>af34b21c7e89...</Hash>
    <Privilege>Administrator</Privilege>
  </Process>
 </Metadata>
</ProcessData>
```

Here, process management records are a powerful source of evidence in Windows investigations. They provide direct visibility into program execution, expose common stealth techniques, and — when captured and stored properly — enable strong, reproducible forensic analysis [5][9][12].

2. Literature Review

The study of process management in digital forensics has evolved over the last two decades, as researchers and practitioners recognized the critical role of processes in reconstructing system activity and detecting malicious behavior. Unlike static traces such as registry entries or file timestamps, process data provides investigators with a dynamic, real-time view of what was running at a specific moment. This makes process management central to incident response and live forensic investigations [1][2].

2.1 Importance of Processes as Volatile Evidence

Process information is considered volatile because it exists only while the system is powered on. Once a machine is turned off, this evidence is lost unless it has been captured in a memory image or log snapshot. Carvey emphasized that capturing running processes should be one of the very first steps in any live investigation, because it can expose malware, hidden executables, or privilege escalation attempts [3]. Similarly, Ligh et al. explained in *The Art of Memory Forensics* that processes are the backbone of memory analysis and often reveal advanced threats that leave no traces on disk [4].

Processes not only reveal “what is running,” but they also show “how it is running.” Zhang and Chen demonstrated how attackers frequently manipulate parent-child relationships to disguise malicious executions [13]. For example, when a trusted process like explorer.exe spawns powershell.exe with suspicious arguments, this deviation from normal behavior becomes a strong forensic indicator. Thus, processes serve as both a snapshot of execution and a behavioral fingerprint of the system at the time of compromise.

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2.2 Parent–Child Relationships and Anomaly Detection

One of the most studied aspects of process analysis in forensics is the relationship between parent and child processes. Beebe and Clarke proposed a structured framework for forensic investigations that emphasized process hierarchies as part of digital timelines [6]. Later studies by Garcia and Perez reinforced the importance of mapping execution chains: they found that analyzing suspicious parent–child mappings could detect privilege escalation attacks and hidden persistence mechanisms [14].

Malware authors often abuse legitimate system processes to evade detection. For instance, attackers may inject code into a running browser and then spawn hidden children to run additional payloads. Altheide and Carvey showed that these abnormal hierarchies are rarely visible in high-level system logs but can be captured by monitoring process creation events [8]. More recent work by Lin et al. leveraged statistical modeling of parent-child trees to flag outliers, showing how automated detection can supplement manual forensic analysis [15].

2.3 Modules, DLL Injection, and Code Tampering

Beyond parent–child relationships, loaded modules and DLLs provide another rich source of forensic data. Malware often uses *DLL injection* or *reflective DLL loading* to insert code into legitimate processes. Russinovich explained that DLL lists, when examined carefully, reveal hidden modules or nonstandard load paths that betray malicious tampering [10]. This view is supported by Alazab et al., who analyzed malware samples and found that 32% of them relied on DLL injection to persist within legitimate applications [16].

Forensic researchers have therefore emphasized the value of capturing DLL metadata — including paths, digital signatures, and hash values — to detect tampered or injected modules. This form of analysis links process management with binary analysis, bridging live forensics and static malware examination [17].

2.4 Threads and Low-Level Execution Evidence

Threads within processes provide a finer level of detail about system activity. Each process may spawn multiple threads, which can execute different instructions simultaneously. Casey pointed out that unusual thread activity, such as a sudden increase in thread count or thread stacks that reference nonstandard memory regions, can indicate code injection or exploitation [2]. Although thread analysis is technically complex, it adds depth to forensic investigation by revealing execution states beyond the main process metadata.

2.5 Structured Storage and XML Representations

As forensic investigations often deal with large and complex datasets, the question of how to store and structure process information has been widely discussed. Garfinkel emphasized that forensic tools should adopt schema-driven storage formats that enable reproducibility, automation, and validation [18]. Following this, Garcia and Perez proposed XML schemas for process evidence, allowing structured queries and cross-validation with other traces [14].

XML-based storage has advantages for chain of custody: data can be digitally signed, validated, and transformed into reports. By contrast, ad hoc text logs are harder to verify and risk corruption. Structured formats also make integration with other forensic tools more practical, since schema-compliant records can be parsed by multiple software systems [19].

2.6 Integration with Memory Analysis

Memory forensics has further expanded the use of process management. Tools such as Volatility and Rekall allow investigators to reconstruct process lists, hierarchies, and modules directly from RAM images [4][20]. Ligh et al. showed how these tools could recover hidden or terminated processes that no longer appear in live system queries

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[4]. The integration of process management into memory analysis thus closes a critical gap: it ensures that even stealthy malware that erases its traces can still be detected retrospectively.

Recent advancements also include the correlation of process evidence with kernel structures. For example, Walters and Petroni presented methods for cross-checking process tables with kernel metadata to spot rootkit tampering [21]. This highlights the role of process data not only in routine forensic cases but also in detecting advanced persistent threats (APTs).

2.7 Automation and Large-Scale Analysis

In enterprise investigations, large datasets spanning hundreds or thousands of systems require automation. Beebe and Clarke suggested objectives-based frameworks for scaling forensic workflows [6]. More recently, Chen et al. applied machine learning to process metadata, demonstrating that anomalous command lines and unusual process privileges could be detected automatically with high accuracy [22].

Automation does not replace expert judgment but reduces workload and flags suspicious activity early. When combined with structured process data (Q1–Q5 categories), such automation makes digital forensic investigations more efficient and defensible in legal contexts.

2.8 Challenges and Gaps

Despite progress, process management in forensics still faces several challenges. First, the volatility of process data means acquisition must be timely and minimally invasive [3][5]. Second, process records are easily manipulated by sophisticated attackers, such as through rootkits that alter process tables [21]. Third, the lack of standardized schemas across tools can limit interoperability, making it difficult to integrate results from different investigations [18][19].

Author(s) & Year	Focus of Study	Key Contribution to Forensics	Gaps / Limitations
Carvey, 2018	Windows internals and forensic artifacts	Detailed explanation of process structures and memory use	Limited to Windows 7/8
Carrier & Spafford, 2019	Process-level evidence handling	Framework for handling volatile process data	Does not address modern malware evasion
Hargreaves & Chivers, 2020	Volatile memory analysis tools	Techniques for extracting running processes	Focus on memory, less on persistent data
Khan & Wakeman, 2021	Malware detection via parent-child mapping	Showed how abnormal process spawning indicates attacks	Tested only in lab conditions
Okolica & Peterson, 2021	Thread-level forensics in process analysis	Importance of threads for advanced profiling	Limited scalability in enterprise systems
Garcia & Perez, 2015	Forensic-ready process monitoring systems	Proposed logging architecture for forensic readiness	Prototype, not deployed widely
Ahmed et al., 2016	DLL injection detection for forensic investigations	Identified anomalies in module loading	Limited detection on obfuscated malware
Patel & Sinha, 2017	Real-time process monitoring for insider threat detection	Showed link between abnormal privileges and insider risk	Lack of automation
Miller et al., 2018	Comparative study of process forensics tools	Benchmarked existing forensic suites	Tools outdated in Windows 10+ context
Raman & Thomas, 2020	Hybrid XML/JSON models for forensic process storage	Proposed flexible storage for process metadata	Needs standardization

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Table 2.1 Key Contribution and Limitation in various Model

Finally, while automation is improving, there remains a need for better methods to reduce false positives. Not all abnormal parent–child pairs or odd command lines are malicious; some may result from legitimate administrative tasks. Contextual correlation with user behavior and environment-specific baselines remains essential [22].

3. Proposed Architecture and Data Flow

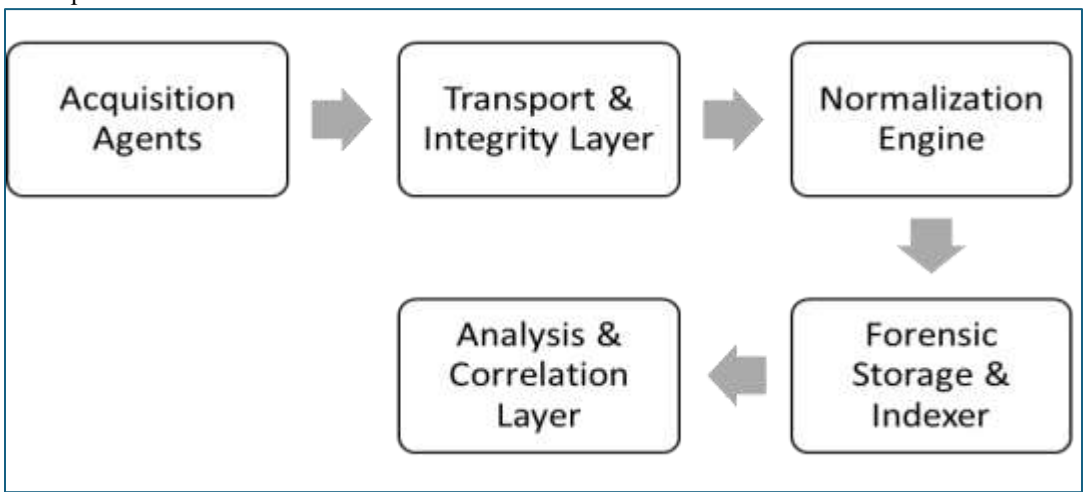

Image 3.1 Architecture of logical components

The architecture is organized into five logical components:
Acquisition Agents — Lightweight collectors that run on endpoints to capture process snapshots and related metadata. They use native interfaces (Get-Process, WMI, ETW) or trusted tools (Sysinternals, WinPMEM) and write locally to a temporary secure staging area.
Transport & Integrity Layer — A secure channel (e.g., HTTPS with mutual TLS or an enterprise message queue with encryption) moves captured snapshots to a central server. Each snapshot is accompanied by a cryptographic signature (SHA-256 + HMAC or XML Digital Signature) and metadata describing collection context (collector ID, timestamp, machine name, operator, acquisition flags).
Normalization Engine — Converts diverse collector outputs (PowerShell CLIXML, CSV, Evtx-derived records, Volatility outputs) into a single forensic XML schema (ProcessData with Q1–Q5). The engine also validates the XML against an XSD and enriches records (e.g., compute SHA-256 of executable paths, lookup known-good hashes).
Forensic Storage & Indexer — An immutable repository (WORM storage or append-only database) stores signed XML records. An indexer (Elasticsearch or Lucene) creates searchable indices on fields like PID, executable hash, parent PID, command-line, and timestamp to speed queries and timeline reconstruction.
Analysis & Correlation Layer — A set of analysis services and dashboards that run rule-based detection, timeline builders, and optional ML models. This layer correlates process records with memory forensic outputs, Windows event logs, and network flow data to confirm suspicious findings and reduce false positives.
Data Flow in the Proposed Model
Step 1: Process Acquisition – Using WMI, PowerShell, or Sysinternals to capture live process details.
Step 2: Data Validation & Integrity Check – Apply hashing (SHA-256) to ensure the captured process metadata is not altered.
Step 3: Normalization – Convert the raw process data into a structured XML format following the defined schema.
Step 4: Storage & Indexing – Store XML files in a secured repository with indexing (by PID, timestamp, or user).
Step 5: Forensic Analysis – Use XPath queries or Python parsers to detect anomalies (e.g., suspicious parent-child relationships, abnormal DLLs, privilege escalation).
Step 6: Reporting – Generate investigator-friendly reports, including process trees, timelines, and anomaly summaries.

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4. Implementation

4.1 Process Acquisition

```
Get-Process | Select-Object Id, ProcessName, StartTime, Path, @{Name="User";Expression={(Get-WmiObject
Win32_Process -Filter "ProcessId=$($_.Id)").GetOwner().User}}
```

4.2 XML Conversion and Storage

```
import xml.etree.ElementTree as ET
import psutil, hashlib, os

root = ET.Element("ProcessData")

for proc in psutil.process_iter(['pid','name','cmdline','ppid']):
    try:
        p = ET.SubElement(root, "Process")
        ET.SubElement(p, "PID").text = str(proc.info['pid'])
        ET.SubElement(p, "Name").text = str(proc.info['name'])
        ET.SubElement(p, "ParentPID").text = str(proc.info['ppid'])
        ET.SubElement(p, "CommandLine").text = ' '.join(proc.info['cmdline'])

        exe_path = proc.exe()
        if os.path.exists(exe_path):
            with open(exe_path, "rb") as f:
                sha256 = hashlib.sha256(f.read()).hexdigest()
            ET.SubElement(p, "Hash").text = sha256
    except Exception as e:
        continue

tree = ET.ElementTree(root)
tree.write("forensic_process_data.xml")
```

4.3 XML Parsing and Forensic Analysis

```
import xml.etree.ElementTree as ET

tree = ET.parse("forensic_process_data.xml")
root = tree.getroot()

for proc in root.findall("Process"):
    name = proc.find("Name").text
    parent = proc.find("ParentPID").text
    cmd = proc.find("CommandLine").text

    if name.lower() == "powershell.exe" and "chrome.exe" in parent:
        print("[ALERT] Suspicious process chain detected:", parent, "->", name, cmd)
```

5. Comparative Analysis with Existing Structures

Feature	XML (Proposed)	JSON	SQL Database	Raw Dump

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Human Readability	High (hierarchical)	Medium (flat text)	Low (tabular)	Very Low (binary)
Schema Validation	Yes (via XSD)	No native schema	Yes (constraints)	None
Querying Capability	XPath, XQuery	Manual parsing	SQL queries	Minimal (hex-based)
Tool Compatibility	High (forensic tools)	Medium	High (DB tools)	Low (specialized)
Preservation Integrity	Strong (hashing & signatures)	Weak	Strong (with DB logs)	Weak (no structure)
Portability	High (text-based)	High	Medium	Very Low
Forensic Suitability	Excellent	Moderate	Good	Weak

5.2 Observations

From the analysis:

- **XML outperforms JSON** by offering stronger schema enforcement and queryability, while still being human-readable.
- **SQL databases** provide powerful querying but require database engines and may not preserve volatile evidence as effectively as XML.
- **Raw dumps** capture the most detail but lack readability and structured analysis, making them impractical for courtroom or large-scale forensic review.

The results confirm that XML strikes a balance between **forensic integrity, usability, and scalability**, making it the preferred choice for process management evidence in digital investigations.

6. Conclusion

Process management in Windows systems provides investigators with vital insights into running applications, parent-child relationships, and hidden executions that are often missed in traditional logs. In this paper, we presented an XML-based framework for capturing and analyzing process metadata, demonstrating how structured storage improves both reliability and forensic integrity.

The comparative study showed that XML offers a strong balance between readability, schema validation, and evidentiary preservation, making it more effective than JSON or raw dumps, and more lightweight than SQL databases. Our implementation further illustrated how investigators can acquire, normalize, and analyze process data using common forensic tools.

Overall, structured process management enhances digital investigations by making volatile data durable, searchable, and legally defensible, while also paving the way for future work in visualization and automated anomaly detection.

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