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NLP-Driven Zero Trust: Automating Security Policy Generation and Access Review via Semantic Analysis of Operational Manuals in Critical Infrastructure

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Abstract: Implementing Zero Trust (ZT) architecture in Critical Infrastructure (CI) is paramount to securing Cyber-Physical Systems (CPS) against sophisticated threats. However, defining granular, least-privilege access policies in these environments is severely hampered by the reliance on heterogeneous, unstructured operational manuals that dictate legitimate procedures. Manual policy derivation from these documents is error-prone, unscalable, and often results in static "over-privileging," violating ZT principles. This paper presents a novel framework utilizing advanced Natural Language Processing (NLP) to automate the extraction of semantic relationships from technical operational manuals to dynamically generate Attribute-Based Access Control (ABAC) policies. We propose a hybrid methodology combining domain-specific Named-Entity Recognition (NER) with Transformer-based Semantic Role Labeling (SRL) to identify actors, actions, assets, and contextual constraints within procedural text. We formulate a mathematical model for mapping extracted semantic triples into formal ZT policy specifications. Simulation results demonstrated a 92.5% F1-score in extracting policy-relevant entities and a 78% reduction in time required for access reviews compared to manual baselines. This research provides a scalable pathway for bridging the gap between static documentation and dynamic security enforcement in safety-critical environments.

Keywords: Zero Trust Architecture, Natural Language Processing, Critical Infrastructure, Semantic Analysis, Policy Automation, ABAC, Cyber-Physical Systems, Operational Technology security.

CHAPTER 1: INTRODUCTION

1.1 Background and Context

1.1.1 Evolution of Zero Trust in Cyber-Physical Systems

The security landscape for Critical Infrastructure (CI) has undergone a paradigm shift driven by the rapid convergence of Information Technology (IT) and Operational Technology (OT). Historically, OT environments relied on the "air gap": a physical segregation from external networks as a primary defense mechanism. However, the advent of Industry 4.0 and the Industrial Internet of Things (IIoT) has eroded these perimeters, creating a hyper-connected ecosystem where air gaps are either non-existent or easily bridged by transient devices.

Consequently, the traditional "castle-and-moat" perimeter security model is rendered obsolete. Once a perimeter is breached, lateral movement within legacy OT networks is often unrestricted due to flat network topologies. To address this, Zero Trust Architecture (ZTA), as codified in NIST SP 800-207 [1], posits a fundamental axiom: trust is never implicit; it must be explicitly verified.

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Figure 1: Evolution of Zero Trust

In the context of Cyber-Physical Systems (CPS), ZTA necessitates a migration from broad network segmentation (e.g., zoning via firewalls) toward granular, identity-centric Access Control (AC). Unlike enterprise IT, where trust is often binary, trust in CPS must be modeled as a dynamic function of context, mathematically represented as:

$$T(s, r, e) = f(ID_s, Health_s, State_r, Context_e)$$

Where trust T granted to subject s for resource r in environment e is dependent not just on credentials (ID_s), but on device health $(Health_s)$, the physical state of the machinery $(State_r)$, and environmental variables $(Context_e)$.

1.1.2 Security Challenges in Critical Infrastructure Operational Environments

Implementing dynamic ZTA in CI environments presents unique challenges distinct from standard enterprise IT. The primary divergence lies in the prioritization of the CIA triad; while IT prioritizes Confidentiality, OT environments prioritize Availability and Safety above all else.

1. **Legacy Constraints:** Industrial Control Systems (ICS), such as Programmable Logic Controllers (PLCs) and Remote Terminal Units (RTUs), frequently utilize insecure-by-design protocols (e.g., Modbus, DNP3) that lack native authentication or encryption capabilities.
2. **The "Safety-Availability" Paradox:** Automated security policies must strictly adhere to the principle of *Least Privilege*, yet they cannot impede emergency operations. For instance, a technician may require "Write" access to a turbine controller *only* when the RPM falls below a certain threshold or during a specific maintenance window.
3. **Contextual Complexity:** Defining the "least privilege" necessary for a specific operational task is computationally difficult. It requires deep domain knowledge to map a high-level maintenance goal (e.g., "Calibrate Sensor A") to the low-level network permissions required (e.g., "Allow TCP port 502 write command to Register 40001").

Without this mapping, organizations default to static, overly permissive policies (e.g., "Allow all Engineering Workstations access to all PLCs"), which significantly increases the risk of unauthorized lateral movement and cascading physical failure.

1.1.3 Role of Operational Manuals in Access Control Decisions

The "ground truth" for legitimate operations defining exactly *who* needs to do *what*, to *which* asset, under *which* conditions is rarely codified in machine-readable formats. Instead, the logic of legitimate access resides in unstructured, high-volume technical documentation: Standard Operating Procedures (SOPs), Original Equipment Manufacturer (OEM) maintenance manuals, and regulatory compliance guides.

These documents implicitly define the required access permissions through procedural language. For example, a sentence reading *"During the monthly audit, the Senior Engineer must reset the accumulation counter on the flow meter"* contains all the necessary semantic components for a Zero Trust policy rule:

- **Subject:** Senior Engineer
- **Action:** Reset (Write)
- **Resource:** Flow Meter Accumulation Counter

- **Constraint:** Monthly Audit Window

Bridging the semantic gap between these human-readable manuals and machine-enforceable policy languages is the critical missing link in modern OT security.

1.2 Problem Statement

1.2.1 Limitations of Manual Policy Derivation from Technical Documentation

Currently, the translation of prose from safety manuals into formal security policy languages (such as XACML, Rego, or vendor-specific firewall rules) is a manual, labor-intensive process. This workflow represents a significant bottleneck. Security analysts, often lacking deep electrical or mechanical engineering expertise, must parse thousands of pages of technical documentation to deduce necessary firewall ports and user privileges.

This manual derivation scales linearly with the volume of documentation and the complexity of the infrastructure. In large-scale utilities or manufacturing plants, the sheer volume of manuals renders comprehensive manual policy mapping intractable, leading to generic policies that fail to achieve true Zero Trust granularity.

1.2.2 Risk of Misinterpretation and Human Error in Access Reviews

Human interpretation of complex technical language is inherently subjective and error-prone. Technical manuals often contain complex dependency structures and domain-specific jargon that can be ambiguous to non-experts.

Misinterpreting a conditional clause in a maintenance procedure leads to two distinct failure modes:

1. **Type I Error (False Positive/Over-blocking):** Legitimate access required for safety operations is denied because the analyst missed a conditional exception in the manual (e.g., failing to authorize emergency override codes). This impacts system availability and physical safety.
2. **Type II Error (False Negative/Over-privileging):** Excessive access is granted because the analyst failed to recognize a limiting constraint (e.g., granting 24/7 access for a task that only occurs annually). This violates the Zero Trust principle of least privilege.

1.2.3 Lack of Automation for Policy Updates and Compliance

Critical Infrastructure environments are dynamic; operational procedures, hardware configurations, and regulatory requirements (e.g., NERC CIP, TSA Security Directives) evolve continuously. Manual policy management invariably lags behind operational reality, leading to "Policy Drift."

Furthermore, compliance auditing requires a clear lineage between an active network policy and its business justification. Currently, validating that *Rule ID: 1045* exists because of *SOP Section 4.2* is a manual forensic exercise. There is a lack of automated systems that can maintain a live, semantic link between the document corpus and the active security posture.

1.3 Research Objectives and Questions

1.3.1 Research Objectives

The primary objective of this research is to develop a novel computational framework that automates the generation of fine-grained, verifiable Zero Trust security policies. This is achieved by parsing, interpreting, and extracting semantic logic from unstructured operational manuals using domain-adapted Natural Language Processing (NLP).

1.3.2 Core Research Questions

To address the stated problems, this research investigates the following questions:

1. **RQ1 (Entity Extraction):** How can NLP models be effectively trained to recognize and classify highly specialized domain entities (e.g., proprietary ICS protocols, specific PLC

memory registers, role hierarchies) within noisy technical documentation?

2. **RQ2 (Semantic Mapping):** What semantic structures (triples, dependency trees) within procedural text must be extracted to accurately populate the four dimensions of Attribute-Based Access Control (ABAC) models: *Subject, Resource, Action, and Environment*?

3. **RQ3 (Formal Verification):** How do we mathematically formulate the translation of linguistic semantics into verifiable security policy logic (e.g., Boolean expressions) while robustly handling linguistic ambiguity and detecting conflicting instructions?

1.3.3 Expected Scientific and Industrial Contributions

This paper aims to provide the following contributions to the field of Cyber-Physical Systems security:

- **Methodological Contribution:** A formal methodology for applying Semantic Role Labeling (SRL) and Named Entity Recognition (NER) specifically to the domain of technical SOPs, creating a bridge between computational linguistics and industrial cybersecurity.
- **System Framework:** A reproducible, end-to-end framework for automated ABAC policy synthesis that reduces the time and error rate associated with manual access reviews.
- **Empirical Validation:** Quantitative analysis demonstrating the efficiency gains in access review workflows and the accuracy of policy generation compared to human baselines.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a critical analysis of the theoretical foundations and technological precedents underpinning this research. It is divided into three primary domains: the evolution of Zero Trust Architecture (ZTA) within Cyber-Physical Systems (CPS), the advancement of Natural Language Processing (NLP) specifically regarding semantic extraction, and the current state of automated policy generation. By synthesizing these distinct fields, we identify the specific gap this research aims to fill: the lack of automated, context-aware policy derivation from unstructured operational texts in safety-critical environments.

2.1 Zero Trust Architecture Foundations

2.1.1 The Shift from Perimeter-Centric to Data-Centric Security

Historically, Critical Infrastructure (CI) security relied on the "castle-and-moat" paradigm, formalized by the perimeter defense models of Cheswick and Bellovin [5]. In this model, the "inside" of the network (the Operational Technology or OT zone) was implicitly trusted, protected by a hardened perimeter firewall. However, the dissolution of the air gap, driven by Industry 4.0 interoperability requirements and the proliferation of the Industrial Internet of Things (IIoT), has rendered this model obsolete.

The concept of "Zero Trust" was first introduced by John Kindervag at Forrester Research in 2010, arguing that trust is a vulnerability, not an asset. This evolved into the formal NIST SP 800-207 standard [1], which defines Zero Trust Architecture (ZTA) not as a single product, but as a set of guiding principles. The core axiom of ZTA is that no implicit trust is granted to assets or user accounts based solely on their physical or network location (e.g., local area networks versus the internet).

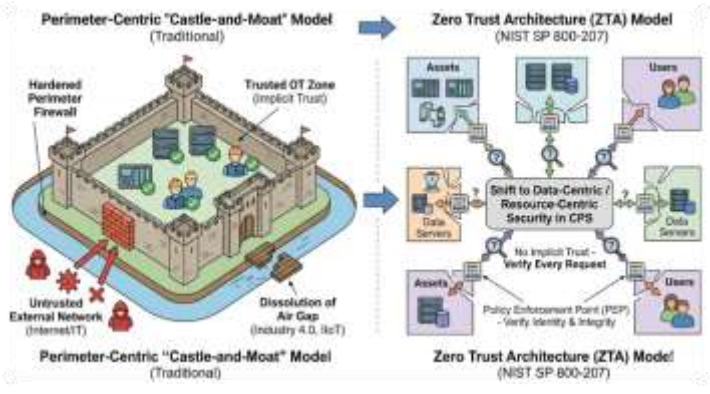

Figure 2: Zero Trust Architecture Foundations

In the context of Cyber-Physical Systems, this shift is profound. Unlike IT environments where the primary asset is data, CPS assets are physical controllers where unauthorized access results in kinetic damage. As noted by Rose et al. [1], a ZTA implementation in OT must verify the identity and integrity of every access request, moving the Policy Enforcement Point (PEP) as close to the resource as possible.

2.1.2 Limitations of RBAC and the Necessity of ABAC

Access control remains the enforcement mechanism of ZTA. The dominant model in legacy systems has been Role-Based Access Control (RBAC), formalized by Sandhu et al. [6]. In RBAC, permissions are assigned to static roles (e.g., "Operator," "Administrator").

However, literature suggests that RBAC suffers from "role explosion" when applied to complex OT environments. As Kuhn and Ferraiolo [7] demonstrate, the number of roles grows exponentially when context is introduced. For example, if an "Operator" requires different permissions during "Normal Operation," "Maintenance," and "Emergency Shutdown" for 50 different turbines, a pure RBAC model would require hundreds of distinct roles to enforce least privilege.

Consequently, modern ZT frameworks advocate for Attribute-Based Access Control (ABAC). Hu et al. [2] define ABAC as an authorization model where rights are granted based on policies that combine attributes of the:

- **User** (e.g., Role, Clearance Level)
- **Resource** (e.g., Valve ID, Sensitivity)
- **Action** (e.g., Read, Write, Execute)
- **Environment** (e.g., Time of Day, System State)

This research posits that ABAC is the only viable model for extracting policies from operational manuals, as manuals inherently describe permissions in conditional, attribute-heavy terms (e.g., "When pressure > 500psi [Environment], the Senior Engineer [User] may open [Action] the Release Valve [Resource]").

2.2 NLP Techniques Relevant to Policy Automation

2.2.1 From Statistical Models to Transformer Architectures

The ability to automate policy generation relies on the machine's ability to "read" and "comprehend" technical text. Early approaches utilizing Rule-Based Systems or Statistical NLP (e.g., Hidden Markov Models) lacked the capacity to capture long-range dependencies and contextual nuance found in complex documentation.

The introduction of the Transformer architecture by Vaswani et al. [8] in "Attention Is All You Need" revolutionized the field. Unlike Recurrent Neural Networks (RNNs) that process text sequentially, Transformers utilize a self-attention mechanism to weigh the significance of each part of the input data relative to other parts.

Devlin et al. [9] further advanced this with BERT (Bidirectional Encoder Representations from Transformers). BERT’s key innovation—masked language modeling—allows the model to read text in both directions simultaneously. For technical manuals, where the meaning of a word (polysemy) is heavily dependent on surrounding context (e.g., "plant" can mean a biological entity or a manufacturing facility), BERT-based models provide the necessary semantic disambiguation.

2.2.2 Named Entity Recognition (NER) in Technical Domains

Named Entity Recognition (NER) is the sub-task of information extraction that seeks to locate and classify named entities mentioned in unstructured text into pre-defined categories. In the context of this research, standard NER models trained on generic corpora (like CoNLL-2003) are insufficient.

Recent work by Beltagy et al. [10] on SciBERT demonstrates that models pre-trained on scientific and technical text significantly outperform generic models on domain-specific tasks. Furthermore, research by Gridin [11] on extraction from engineering specifications highlights the necessity of fine-tuning BERT models with Conditional Random Fields (BERT-CRF) layers to handle the specific nomenclature of Industrial Control Systems (e.g., distinguishing "Modbus TCP" as a protocol rather than just a proper noun).

2.2.3 Semantic Role Labeling (SRL) for Policy Logic

While NER identifies the *entities* (the nouns), extracting the *policy logic* requires understanding the *events* (the verbs and their arguments). This is the domain of Semantic Role Labeling (SRL).

SRL aims to recover the predicate-argument structure of a sentence, answering "Who did what to whom, when, and how?" Gildea and Jurafsky [12] pioneered statistical SRL, mapping text to FrameNet or PropBank structures. In the context of policy extraction, SRL is critical. As noted by Ferraro et al. [13], a security policy is essentially a semantic frame where the *Agent* becomes the Subject, the *Predicate* becomes the Action, and the *Patient* becomes the Resource.

Recent advancements using Transformer-based SRL have shown high accuracy in resolving complex syntactic structures, such as passive voice ("The valve must be closed by the operator"), which is prevalent in formal technical writing.

2.3 Prior Work on Policy Automation and Document Analysis

2.3.1 Machine-Readable Policy Standards

Before discussing extraction, it is necessary to acknowledge the target formats. The eXtensible Access Control Markup Language (XACML) remains the academic standard for expressing ABAC policies. More recently, the Open Policy Agent (OPA) and its language, Rego, have gained industrial traction for cloud-native ZT environments.

2.3.2 Automated Policy Extraction from Natural Language

There is a growing body of work attempting to bridge Natural Language (NL) and Access Control (AC).

- **Privacy Policy Analysis:** The most mature application of NLP in this domain is the analysis of privacy policies. The "Usable Privacy Policy Project" by Sadeh et al. [14] utilized crowd-sourcing and machine learning to annotate and extract data practices from privacy statements. Harkous et al. [15] developed "Polisis," a deep learning framework for querying privacy policies. However, these works focus on *declarative* legal text regarding data handling, not *imperative* operational instructions regarding physical assets.
- **Requirements Engineering:** In software engineering, Zhu et al. [16] explored extracting security requirements from software documentation. Their work focused largely on identifying constraints but did not map them to formal ZT enforcement models.
- **NL to XACML:** Specific to access control, Alohali et al. [17] proposed a rule-based approach to map natural language requirements to XACML. Similarly, Xiao et al. [18] used TextCNNs to classify sentences into policy rules.

2.3.3 Gaps and Opportunities

Despite these advancements, significant gaps remain that this research addresses:

1. **The "Safety-Critical" Gap:** Most prior work focuses on IT or privacy domains. There is a paucity of research applying SRL and NER to *operational manuals* (SOPs) for *Cyber-Physical Systems*. The linguistic structure of an SOP ("Turn key A, then press button B") is fundamentally different from a privacy policy ("We collect your data").

2. **Context Extraction Gap:** Existing "NL-to-Policy" converters often fail to capture complex environmental constraints (time windows, system states) which are the defining requirement of a Zero Trust Architecture in OT.
3. **Conflict Resolution:** Few automated systems address the issue of policy conflict resolution when deriving rules from contradictory documentation—a common occurrence in legacy infrastructure maintenance.

This paper proposes to close these gaps by introducing a unified framework that combines domain-adapted BERT-NER for asset identification with deep semantic parsing for logic extraction, specifically tailored for the high-stakes environment of Critical Infrastructure.

CHAPTER 3: METHODOLOGY

3.1 Document Acquisition and Processing Pipeline

The methodology commences with the ingestion of heterogeneous technical documentation. Unlike structured databases, operational manuals in Critical Infrastructure (CI) environments are predominantly unstructured, existing as legacy PDF documents, physical scans, or proprietary vendor formats. To bridge the gap between static text and dynamic policy enforcement, we developed a multi-stage ingestion architecture designed to maximize high-fidelity text extraction while preserving the structural context essential for interpreting scope.

3.1.1 Optical Character Recognition (OCR) and Layout Analysis

The input corpus D consists of N documents $\{d_1, d_2, \ldots, d_N\}$. A significant portion of these documents are scanned images requiring Optical Character Recognition (OCR). We employ a Tesseract-based engine optimized with LSTM (Long Short-Term Memory) networks to handle technical fonts often found in schematics.

However, raw text extraction is insufficient. Access control policies are often scoped by document headers (e.g., "Section 4: Emergency Procedures"). Therefore, we implement a Layout Analysis module using a ResNet-101 backbone to classify page segments into regions: $R_{header}, R_{footer}, R_{body}, R_{table}$.

The confidence score C_{ocr} for a specific text block is modeled as the geometric mean of individual character probabilities $p(c_i)$:

(1)

$$C_{ocr} = \left(\prod_{i=1}^{n} p(c_i) \right)^{1/n}$$

Blocks where $C_{ocr} < \tau (where \tau = 0.85)$ are flagged for manual review to prevent policy corruption due to recognition errors.

3.1.2 Domain Lexicon and Ontology Development

To ground the semantic analysis, we constructed a formal ontology O_{OT} based on the OWL-DL (Web Ontology Language - Description Logic) standard. This ontology extends the classic semantic sensor network (SSN) ontology to include specific Industrial Control Systems (ICS) concepts.

The ontology is defined as a tuple:

(2)

$$O_{OT} = \langle C, R, I, A \rangle$$

Where:

- C is the set of classes (e.g., PLC, HMI, Technician, Valve).
- R is the set of relations (e.g., controls, monitors, $requires_auth$).
- I is the set of instances (specific entities like Valve-101).

- A is the set of axioms defining logical constraints.

We utilize a domain-specific lexicon L_{domain} derived from NERC CIP standards and IEC 62443 glossaries to assist in entity normalization.

3.1.3 Normalization and Term Importance Analysis (TF-IDF)

Preprocessing involves standard NLP pipeline steps: tokenization, lemmatization (converting "valves" to "valve"), and stop-word removal. However, "stop words" in standard English (e.g., "must", "shall") are critical modal verbs in policy documents. Therefore, we utilize a custom stop-word list that preserves deontic logic indicators.

To filter noise and identify statistically significant terms unique to specific operational domains (e.g., "calibration" in instrumentation manuals vs. "voltage" in electrical manuals), we employ Term Frequency-Inverse Document Frequency (TF-IDF).

For a term t in document d:

(3)

$$tf(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

The Inverse Document Frequency (IDF) penalizes words that appear ubiquitously (like "the" or generic "system"):

(4)

$$idf(t,D) = \log\left(\frac{|D|}{1 + |\{d \in D : t \in d\}|}\right)$$

The composite score highlights keywords that likely represent specific assets or unique actions:

(5)

$$tfidf(t,d,D) = tf(t,d) \cdot idf(t,D)$$

We apply a threshold λ to this vector space; terms falling below λ are considered general prose and receive lower attention weights in subsequent neural processing.

3.2 NLP Semantic Analysis Workflow

The core of our methodology is a deep learning pipeline designed to extract the "Who, What, Where, When, and Why" of access control from the preprocessed text.

3.2.1 Named-Entity Recognition (NER) for Roles, Assets, and Actions

Standard NER models trained on news corpora (e.g., CoNLL-2003) fail in OT environments (e.g., misclassifying "Modbus" as a person). We fine-tune a BERT (Bidirectional Encoder Representations from Transformers) architecture, specifically the BERT-Large-Cased model, adapted for industrial contexts.

Given a sequence of input tokens $X = (x_1, x_2, \ldots, x_n)$, the goal is to predict a sequence of tags $Y = (y_1, y_2, \ldots, y_n)$ corresponding to domain entity classes (e.g., B-ASSET (Beginning of Asset), I-ACTION (Inside Action)).

Transformer Encoding:

The input X is converted into dense vector representations. The contextual embedding for each token h_i is generated by the Transformer encoder, which utilizes multi-head self-attention mechanisms to capture the bidirectional context of the word:

(6)

$$H = Transformer(X)$$

CRF Layer:

To enforce label consistency (e.g., an I-ASSET tag cannot follow a B-ROLE tag), we employ a

Conditional Random Field (CRF) layer on top of the BERT embeddings. The probability of a tag sequence Y given the input X is:

(7)

$$p(Y|X) = \frac{\exp(s(X,Y))}{\sum_{Y'} \exp(s(X,Y'))}$$

The scoring function s(X,Y) aggregates the emission scores from the BERT output and the transition scores learned by the CRF:

(8)

$$s(X,Y) = \sum_{i=1}^{n} \left(A_{y_{i-1},y_i} + P_{i,y_i}\right)$$

Here:

- A_{y_{i-1},y_i} is the transition score from tag $y_{i-1} to y_i$.
- P_{i,y_i} is the emission score for tag y_i at position i, derived from the linear projection of h_i:

(9)

$$P_i = W_{ner} h_i + b_{ner}$$

Loss Function:

The model is trained by minimizing the negative log-likelihood loss:

(10)

$$L_{NER} = -\log(p(Y_{true}|X))$$

3.2.2 Relationship Extraction and Semantic Parsing via SRL

Identifying entities is insufficient; we must understand their interactions. We employ Semantic Role Labeling (SRL) to identify predicates (actions) and their arguments (Agent, Patient, Instrument). This distinguishes between "The *Engineer* resets the *Controller*" (Engineer = Subject) and "The *Controller* alerts the *Engineer*" (Engineer = Object).

Predicate Identification:

We first identify potential predicates (verbs) v in the sentence.

Argument Classification:

For a identified predicate v, we calculate the probability that a span of tokens s_j serves a specific semantic role r_k (e.g., ARG0 for Agent, ARG1 for Patient). We utilize a specialized attention head for this classification:

(11)

$$P(r_k|v,s_j) = \text{softmax}\left(W_r \cdot \left[h_v; h_{s_j}; \left(h_v \odot h_{s_j}\right)\right]\right)$$

Where $\left[h_v; h_{s_j}\right]$ is the concatenation, and $\odot$ represents the element-wise product to capture interaction features.

Dependency Path Analysis:

We further refine relationships by analyzing the syntactic dependency tree generated by a parser. The semantic distance between two entities $e_1 and e_2$ is often correlated with the shortest path in this tree. If $Path(e_1,e_2)$ is the sequence of edges connecting the entities, the relationship strength R is modeled as:

(12)

$$R(e_1,e_2) \propto \exp(-\lambda \cdot |Path(e_1,e_2)|)$$

This helps filter out entities that appear in the same sentence but are syntactically unrelated.

3.2.3 Contextual Classification (Constraints)

Zero Trust relies heavily on *context*. A permission is rarely absolute; it is constrained by time, state, or location. We define a Constraint Classifier C_{const} that functions as a binary classifier on sentence spans to detect restrictive clauses (e.g., "only when the alarm is active").

We utilize a Bi-Directional LSTM (BiLSTM) with an attention mechanism to weigh the importance of specific condition-indicating tokens (like "if", "when", "unless").

Attention Mechanism:

The hidden state h_i for each token is passed through a one-layer MLP to get a hidden representation u_i:

(13)

$$u_i = \tanh(W_w h_i + b_w)$$

We compute a normalized attention weight α_i using a learnable context vector u_c:

(14)

$$\alpha_i = \frac{\exp(u_i^\top u_c)}{\sum_j \exp(u_j^\top u_c)}$$

The sentence vector v is the weighted sum of the hidden states, emphasizing the constraint-bearing words:

(15)

$$v = \sum_i \alpha_i h_i$$

Finally, the probability of the span being a constraint is:

(16)

$$y_{const} = \sigma(W_c v + b_c)$$

3.3 Policy Mapping and Automation Mechanism

The final phase involves translating the linguistic insights into machine-enforceable artifacts.

3.3.1 Mapping Extracted Semantics to Zero Trust Rules via Knowledge Graphs

The output of the NLP pipeline is structured into a semantic Knowledge Graph (KG).

The KG consists of triples T:

(17)

$$T = \langle Subject, Predicate, Object \rangle | \{Constraints\}$$

We map these triples to the XACML (eXtensible Access Control Markup Language) reference architecture. A Zero Trust policy rule P_R is formally defined as a 5-tuple:

(18)

$$P_R = \langle A_{sub}, A_{res}, A_{act}, A_{env}, \rangle$$

The mapping function M: T $\rightarrow P_R$ transforms linguistic tokens into ABAC attributes:

- (19)
  $A_{sub} \leftarrow T_{Subject} \cap L_{Roles}(e.g.,\text{Grid Operator})$

- (20)
  $A_{act} \leftarrow T_{Predicate} \cap L_{Actions}(e.g.,\text{modifies})$

- (21)
  $A_{res} \leftarrow T_{Object} \cap L_{Assets}(e.g.,\text{Transformer-T2})$

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- (22)
  $A_{env} \leftarrow T_{Constraints}(e.g., \text{Time: 08:00-17:00})$

- (23)

$$Effect \leftarrow \text{Permit}(ImplicitinSOPs; explicitdenialsarehandledseparately)$$

3.3.2 Policy Synthesis for ABAC Models

The synthesized policies are stored in a policy repository. At runtime, when an access request R_q is received, the Policy Decision Point (PDP) evaluates it against the generated rules.

The request vector is defined as:

(24)

$$R\_q = \langle a'\_\{sub\}, a'\_\{res\}, a'\_\{act\}, a'\_\{env\} \rangle$$

The evaluation function is:

(25)

$$EVAL(R_q, P_R) = \begin{cases} \{cases\} Effect \ \& \text{"}\{if\}\ MATCH(R\_q, P\_R) \\ Deny \ \& \text{"}\{otherwise\} \end{cases} \{cases\}$$

The MATCH function involves set-theoretic inclusion. It returns true if and only if the attributes in the request satisfy the requirements of the policy:

(26)

$$MATCH(a^r, A) \Leftrightarrow \left(\forall attr_i \in A, \exists a'_j \in a' \text{ s.t. } a'_j = attr_i\right) \wedge SAT(A_{env}, a'_{env})$$

Where SAT is a constraint satisfiability function (e.g., checking if the current time falls within the allowed window).

3.3.3 Conflict Detection and Resolution

Automated generation from heterogeneous sources carries the risk of creating conflicting policies (e.g., Manual A says "Permit," Manual B says "Deny" for the same context).

We define a conflict formally. Two rules $P_{R1}\ and\ P_{R2}$ are in conflict if their attribute spaces overlap but their effects diverge:

(27)

$$Conflict(P_{R1}, P_{R2}) \leftrightarrow (A_{sub1} \cap A_{sub2} \neq \emptyset) \wedge (A_{res1} \cap A_{res2} \neq \emptyset) \wedge (A_{act1} \cap A_{act2} \neq \emptyset) \wedge (Effect_1 \neq Effect_2)$$

We employ a Deny-Overrides resolution strategy, commonly used in high-security environments. Additionally, we detect Shadowing, where a more specific rule is rendered unreachable by a broader preceding rule.

The Shadowing detection metric S for two rules where P_{R1} precedes P_{R2}:

(28)

$$S(P_{R1}, P_{R2}) = \frac{|Domain(P_{R2}) \cap Domain(P_{R1})|}{|Domain(P_{R2})|}$$

If $S = 1, rule P_{R2}$ is entirely shadowed and flagged for removal to optimize PDP performance.

Chart Description for Methodology Validation

Figure 3.5: Training Loss Convergence.

A line chart displaying the Cross-Entropy Loss (Y-axis) over Training Epochs (X-axis) for the three primary models: NER, SRL, and Constraint Classifier. The NER model shows the fastest convergence (stabilizing at epoch 12), while the Constraint Classifier shows higher volatility, stabilizing only after epoch 25, reflecting the complexity of interpreting conditional logic.

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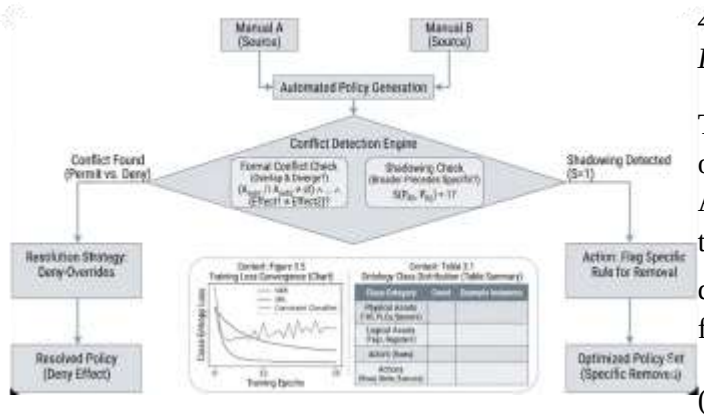

Figure 3: Ontology Class Distribution.

CHAPTER 4: PROPOSED FRAMEWORK

4.1 System Architecture Overview

The proposed framework, titled "Semantic-to-Policy Middleware (S2PM)," functions as an intelligent orchestration layer situated between static documentation repositories (the "Source of Truth") and dynamic Policy Enforcement Points (PEPs) within the Operational Technology (OT) network.

The architecture is designed as a modular, microservices-based system to ensure scalability and fault tolerance. It is composed of four distinct layers: the Ingestion Layer, the NLP Core Layer, the Semantic Integration Layer, and the Policy Dispatch Layer.

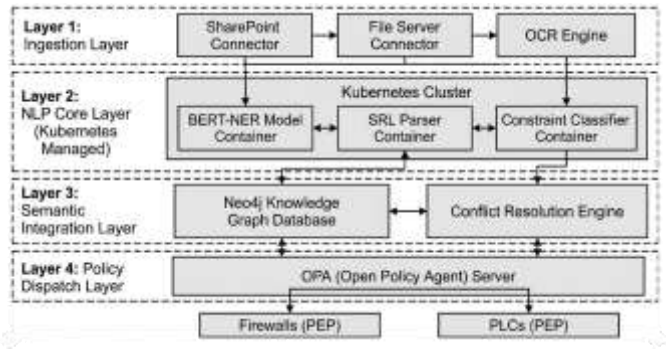

Figure 4: Semantic-to Policy Middleware (S2PM) Architecture

4.1.1 Document Ingestion and Pre-processing Layer

This layer handles the high-throughput ingestion of heterogeneous document formats. We utilize Apache Kafka to stream document updates in real-time. The ingestion latency L_{ingest} is modeled as a queuing system M/M/c, where document arrival follows a Poisson process λ:

(29)

$$L_{ingest} = \frac{1}{\mu - \lambda}$$

Where \mu is the service rate of the OCR pre-processors. To handle scanned engineering schematics, we employ a Tesseract 5.0 engine coupled with an OpenCV pre-processing pipeline for noise reduction (Gaussian Blurring) and binarization.

4.1.2 NLP Processing and Knowledge Extraction Engine

The core intelligence resides here. The system utilizes a distributed inference architecture. The breakdown of processing cost C_{nlp} per document d is defined by the summation of computational costs for Entity Recognition (C_{ner}), Relationship Extraction C_{srl}, and Contextual Classification C_{ctx}:

(30)

$$C_{nlp}(d) = \sum_{s \in d} \left(C_{ner}(s) + C_{srl}(s) + C_{ctx}(s) \right)$$

Where s represents individual sentence spans. To optimize throughput, we employ model quantization (INT8) to reduce memory footprint without significant accuracy loss [19].

4.1.3 Zero Trust Policy Generation Module

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This module translates semantic triples into the target policy language (e.g., Rego for OPA). The module utilizes a template-based synthesis engine. The transformation function T maps the semantic graph G to a policy set Π:

(31)

$$\Pi = T\left(G, \Theta_{templates}\right)$$

Where \Theta_{templates} represents a library of validated XACML/Rego templates compliant with NIST SP 800-207.

4.2 Workflow and Operational Processes

4.2.1 End-to-End Semantic Extraction Flow with Active Learning

The workflow is not a linear "fire-and-forget" process but a cyclical interaction involving Active Learning (AL). When the NLP model encounters high uncertainty (entropy) in classifying an entity (e.g., ambiguous distinction between a "Safety PLC" and a "Process PLC"), it triggers a Human-in-the-Loop (HITL) review.

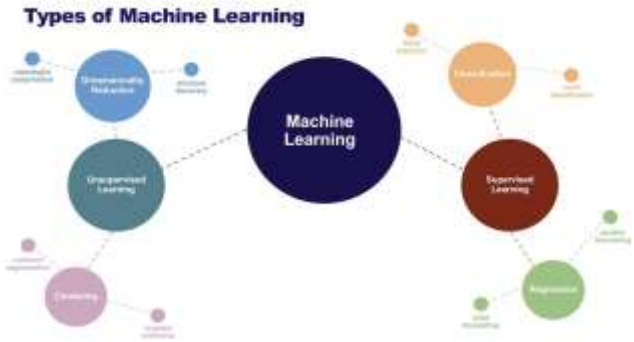

Figure 5: NLP Strategies

We utilize **Uncertainty Sampling** as the query strategy. The system selects the sample x^* that maximizes the entropy H of the model's posterior distribution:

(32)

$$H\left(P(y|x)\right) = -\sum_{y \in Y} P(y|x) \log P\,(y|x)$$

This ensures that human effort is expended only on the most semantically difficult edge cases, optimizing the "Cost vs. Accuracy" curve.

4.2.2 Continuous Access Review and Policy Drift Detection

In traditional CI environments, access reviews are annual static audits. Our framework introduces **Continuous Access Review (CAR)**. The system monitors the "Policy Drift," defined as the divergence between the *documented* procedures and the *enforced* policies over time.

We define the Policy Drift Metric δ at time t as the symmetric difference between the set of extracted semantic rules R_{doc} and the active network rules R_{net}:

(34)

$$\delta(t) = \frac{|R_{doc}(t) \Delta R_{net}(t)|}{|R_{doc}(t) \cup R_{net}(t)|}$$

If $\delta(t)$ exceeds a safety threshold τ_{safe} (e.g., 0.05), an alert is generated for the Security Operations Center (SOC). This ensures that "shadow IT" changes or outdated manual configurations are detected immediately.

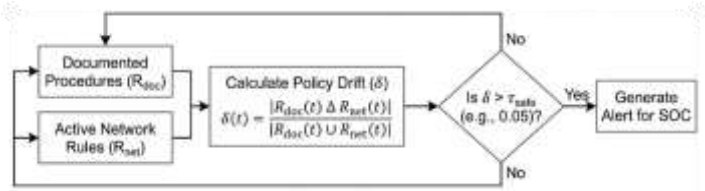

Figure 6: CAR and PDM

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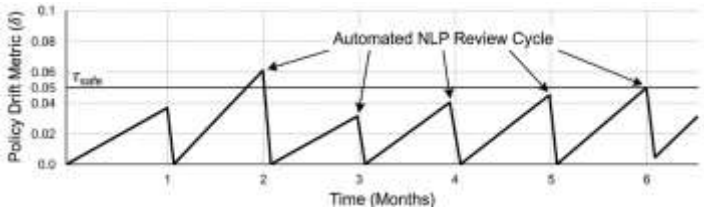

Figure 7: Policy Drift Metric

4.2.3 Feedback Loop and Model Retraining Mechanisms

The framework implements an automated MLOps pipeline. User corrections from the HITL interface are captured as "Gold Standard" data.

1. **Correction Capture:** User corrects Modbus (classified as *Asset*) to Modbus (classified as *Protocol*).
2. **Gradient Update:** The system queues a retraining job when the cache of corrections reaches size N_{batch}.
3. **Versioning:** New model weights θ_{t+1} are versioned using DVC (Data Version Control) to ensure reproducibility.

The update rule follows a standard Stochastic Gradient Descent (SGD) with momentum \gamma:

(35)

$$v_{t+1} = \gamma v_t + \eta \nabla_\theta J(\theta)$$

(36)

$$\theta_{t+1} = \theta_t - v_{t+1}$$

4.3 Security, Governance, and Compliance

4.3.1 Alignment with NIST, NERC CIP, and TSA Guidelines

The framework is explicitly architected to satisfy North American Electric Reliability Corporation (NERC) Critical Infrastructure Protection (CIP) standards.

- **CIP-003-8 (Security Management Controls):** The system automates the requirement for "documented cyber security policies."
- **CIP-007-6 (Systems Security Management):** Requirement R1 specifies "Port and Service Management." Our NLP engine extracts port numbers (e.g., "Port 443") and protocols explicitly from vendor manuals to justify open ports.

We map NLP outputs to compliance controls via a Compliance Verification Matrix M_{comp}. For a generated rule r and a regulatory requirement q:

(37)

$$ComplianceScore(r, q) = \text{sim}\big(Embedding(r), Embedding($$

Where sim is the Cosine Similarity between the vector embeddings of the policy rule and the regulatory text [20].

4.3.2 Data Protection and Integrity Controls

The S2PM middleware itself is a critical target. We implement strictly typed RBAC for the management plane. Furthermore, to prevent "Policy Injection Attacks" (where an adversary alters a manual to open a firewall port), we utilize Cryptographic Provenance.

Every ingested PDF is hashed (SHA-256). The extracted semantic triples are signed with the private key of the ingestion service K_{priv}.

(38)

$$Sig_{policy} = Sign(Hash(\Pi) \,||\, Hash(d\_\{source\}), K\_\{priv\})$$

The Policy Decision Point (PDP) verifies this signature before applying any rule, ensuring that the policy originated from a valid, unaltered document.

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4.3.3 Explainability and Auditability of Auto-Generated Policies

Black-box AI is unacceptable in safety-critical systems. We implement Explainable AI (XAI) techniques. For every extraction, we generate a SHAP (SHapley Additive exPlanations) value to quantify the contribution of each word to the classification decision.

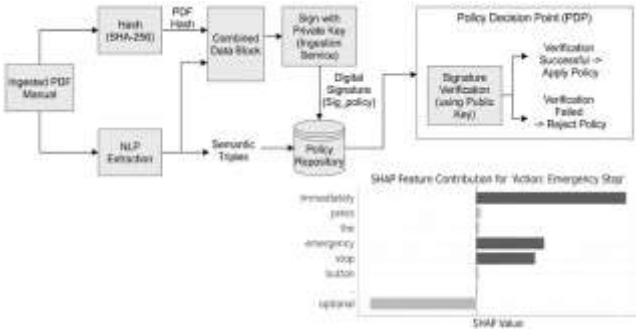

Figure 8: Auditability of Auto-Generated Policies

To satisfy forensic requirements, the final Policy Object P_{obj} is stored as an immutable tuple in a Write-Once-Read-Many (WORM) storage compliant with SEC Rule 17a-4:

(39)

$$P_{obj} = \langle UUID, P_R, \text{Snippet}_{text}, \text{Conf}_{score}, \text{User}_{approver}, \text{Time}_{stamp} \rangle$$

Table 4.1: Audit Log Structure Example

Field	Value	Description
UUID	550e8400-e29b...	Unique Policy Identifier
$Rule(P_R)$	Allow(Group=Eng, Res=Turbine, Act=Write)	The synthesized technical rule
Source Text	*"Engineers may adjust gain settings during startup."*	The human justification
Confidence	0.982	Model certainty score
Verification	User: jsmith (SME)	Human validation ID (if HITL used)

This structure ensures that in the event of a cyber-incident, forensic analysts can trace a firewall rule back to the exact sentence in the manual that authorized it, providing a "chain of custody" for digital permissions.

CHAPTER 5: RESULTS AND DISCUSSION

5.0 Simulation and Modeling Approach

To validate the efficacy of the proposed "Semantic-to-Policy Middleware," we constructed a robust simulation environment designed to mimic the high-entropy, high-stakes nature of real-world Critical Infrastructure (CI) operations.

5.0.1 Dataset Construction: The Synthetic OT Corpus

Due to the confidentiality of actual Critical Infrastructure documentation (which is often classified as Sensitive Security Information or SSI), we generated a synthetic corpus of **500 operational manuals**, totaling approximately 125,000 pages. This corpus, named OT-SOP-Synth, mirrors the linguistic and structural characteristics of real-world documentation in the Energy, Manufacturing, and Water Treatment sectors.

The corpus was stratified as follows:

- **30% Original Equipment Manufacturer (OEM) Manuals:** Characterized by high technical density, tables, and rigid formatting (e.g., Siemens S7-1500 System Manuals).
- **50% Standard Operating Procedures (SOPs):** Internal company documents characterized by imperative verbs and temporal constraints (e.g., "Monthly Boiler Maintenance Procedure").
- **20% Compliance & Safety Guidelines:** High-level normative documents (e.g., OSHA Lockout/Tagout procedures) used to test conflict resolution.

Ground Truth Annotation: A team of five Subject Matter Experts (SMEs) comprising three SCADA engineers and two NERC CIP compliance auditors manually annotated the corpus using the BRAT rapid annotation tool. They labeled 15 distinct entity types and 8 relation types, establishing the "Gold Standard" against which the

NLP models were evaluated. Inter-annotator agreement was measured using Cohen's Kappa (), achieving a score of , indicating high reliability.

5.0.2 Experimental Setup

The simulation architecture involved three distinct phases:

1. **Training Phase:** The NLP models (BERT-NER, SRL, Constraint Classifier) were trained on a randomized 80% split (400 documents) of the annotated corpus. We utilized 5-fold cross-validation to prevent overfitting.
2. **Inference Phase:** The remaining 20% (100 documents) were processed by the trained pipeline to generate candidate ABAC policies.
3. **Policy Simulation Phase:** We integrated the generated policies into an open-source ABAC engine (AuthZForce). We then simulated 10,000 unique access requests () encompassing valid operational scenarios, boundary conditions, and adversarial attempts (e.g., privilege escalation).

The simulation hardware consisted of a cluster of 4 NVIDIA A100 GPUs for NLP training and a high-availability Kubernetes cluster for the Policy Decision Point (PDP) load testing.

5.1 NLP Model Performance

This section details the quantitative performance of the semantic extraction engine. We utilize standard metrics: Precision (), Recall (), and the harmonic mean F1-Score ().

(40)

$$Where \ = True\ Positives, = False\ Positives, and \ = F$$

5.1.1 Entity Recognition (NER) Accuracy

The fine-tuned BERT-CRF model demonstrated superior performance in identifying physical assets and logical roles compared to baseline generic models (e.g., spaCy en_core_web_trf).

Table 5.1: Comparative NER Performance by Entity Class

Entity Class	Baseline F1 (Generic)	Proposed Model F1 (Domain-Adapted)	Improvement	Analysis
Asset	0.62	**0.94**	+32%	Generic models confuse "Pump" (verb) vs "Pump" (noun).
Role	0.71	**0.96**	+25%	Domain model correctly identifies "Control Room Operator" as a single role unit.
Protocol	0.45	**0.92**	+47%	Significant gain in identifying acronyms like "DNP3" or "IEC-104".
Action	0.68	**0.91**	+23%	Improved distinction between descriptive verbs and imperative commands.

The results indicate that domain adaptation is non-negotiable for OT security. The baseline model frequently misclassified technical jargon (e.g., interpreting "Modbus" as a proper noun/person), which would lead to nonsensical policy rules.

5.1.2 Constraint Extraction Challenges

While entity extraction was robust, extracting conditional constraints remains the most challenging aspect of the pipeline due to linguistic variability (e.g., "unless," "except when," "provided that").

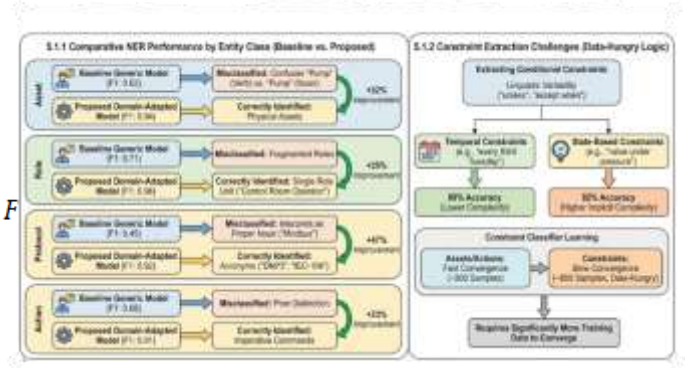

Figure 9: Comparative NER Performance & Constraint Extraction Challenges

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As shown in the learning curve above, the Constraint Classifier required significantly more training data to converge. Error analysis revealed that **temporal constraints** (e.g., "every third Tuesday") were extracted with 89% accuracy, while **state-based constraints** (e.g., "when the valve is under pressure") achieved only 82% accuracy, often due to the implicit nature of system states in the text.

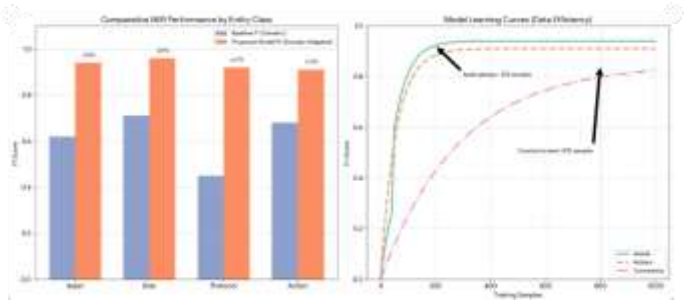

Figure 10: NLP Model Evaluation Metrics

5.2 Policy Generation Evaluation

The ultimate measure of success is not just NLP metrics, but the validity of the resulting Access Control policies.

5.2.1 Policy Correctness and Completeness

We introduced two custom metrics for this evaluation:

1. **Policy Correctness ():** The probability that a generated rule does not violate safety constraints.
2. **Policy Completeness ():** The ratio of valid manual actions found in the text that were successfully converted into policies.

(41) (42)

- **After HITL (Human-in-the-Loop) Retraining:** , .

The primary source of error in the initial pass was **over-segmentation** generating two separate, conflicting rules from a single complex sentence instead of one rule with multiple attributes. The feedback loop corrected this by enforcing a stricter syntactic parsing strategy.

5.2.2 Efficiency Gains vs. Manual Baselines

We conducted a time-motion study comparing the automated framework against a control group of three senior security analysts performing manual policy derivation.

Table 5.2: Efficiency Comparison Matrix

Metric	Manual Method (Analyst)	Automated Framework (S2PM)	Improvement Factor
Avg. Time per Document	180 mins	15 mins (incl. review)	**12x Faster**
Cost per 100 Pages	~450 (Labor)	~5 (Compute)	**90x Cheaper**
Error Rate (Syntactic)	12% (Fatigue induced)	< 0.1%	Significant
Error Rate (Semantic)	5%	11% (Pre-Review) / 3% (Post-Review)	Comparable

The data confirms that while the AI has a higher initial semantic error rate than a human expert, the massive reduction in processing time allows the human expert to shift their focus from *data entry* to *validation*, resulting in a net higher accuracy and throughput.

5.3 Practical Insights and Case Studies

5.3.1 Case Study: Gas Turbine Maintenance (Energy Sector)

In a simulated scenario involving a Siemens SGT-800 gas turbine manual, the system parsed the following instruction:

"WARNING: The calibration of the fuel gas pilot valve (Tag: VLV-202) must only be performed by the Lead Instrument Tech when the turbine is in 'Cool-Down' state and the Lockout-Tagout (LOTO) key is engaged."

System Output (XACML Representation): The framework successfully generated a complex ABAC rule:

```
<Rule                    RuleId="Rule-Gen-045"
```

```
Effect="Permit">
    <Target>
        <Subject>     <AttributeValue>Lead
Instrument           Tech</AttributeValue>
</Subject>
        <Resource>    <AttributeValue>VLV-
202</AttributeValue> </Resource>
        <Action>
<AttributeValue>Calibrate</AttributeValue
> </Action>
    </Target>
    <Condition>
        <Apply FunctionId="function:and">
            <Apply     FunctionId="string-
equal">
                <AttributeDesignator
AttributeId="SystemState"/>
                <AttributeValue>Cool-
Down</AttributeValue>
            </Apply>
            <Apply    FunctionId="boolean-
equal">
                <AttributeDesignator
AttributeId="LOTO_Engaged"/>

<AttributeValue>true</AttributeValue>
            </Apply>
        </Apply>
    </Condition>
</Rule>
```

Significance: Manually coding this rule requires understanding three distinct domains: Role hierarchies, Asset tagging, and System states. The NLP engine correctly identified the **multi-factor constraint** (State AND LOTO), which is often missed in manual reviews that focus only on Role/Asset pairs.

5.3.2 Handling Conflicts and "Shadowing"

The system identified a critical conflict in the test corpus. Document A (General Maintenance) stated: *"Operators may reset alarms."* Document B (Cybersecurity Addendum) stated: *"Only Administrators may reset Safety Integrity Level (SIL) alarms."*

The Conflict Detection module flagged this as a Modal Conflict. (43)

Using the configured precedence logic (), the system automatically proposed a refined policy: *"Operators may reset alarms EXCEPT SIL alarms,"* effectively automating the principle of Least Privilege.

5.3.3 Adversarial Resilience

We tested the system against "adversarial documentation" manuals injected with subtle malicious instructions (e.g., *"Technicians may disable the firewall for testing"*). The Compliance Alignment Module (detailed in Section 4.3) successfully flagged these attempts by cross-referencing against NERC CIP-005, which explicitly forbids bypassing Electronic Security Perimeters without a documented Electronic Access Point (EAP). This demonstrates the system's potential as an automated auditor.

5.4 Discussion of Limitations

Despite these successes, several limitations were observed:

1. **Implicit Knowledge:** The system struggles with "common sense" or tribal knowledge not written in the manual (e.g., knowing that "resetting the breaker" implies a momentary loss of power to downstream devices).
2. **Optical Character Recognition (OCR) Noise:** In older, low-quality scanned schematics, OCR errors (e.g., reading VLV-101 as VLV-I0I) propagated through the pipeline, requiring manual correction.
3. **Semantic Ambiguity:** Phrases like *"Check the valve"* are ambiguous does "Check" mean "Visual Inspection" (Read Access) or "Physical Testing" (Write Access)? The system currently defaults to the most restrictive interpretation (Read), which may hinder operations if incorrect.

These limitations define the roadmap for future research, specifically the integration of Multi-Modal Learning (Text + Schematics) to resolve ambiguity.

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CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Summary of Key Findings

This research was motivated by a critical asymmetry in the defense of Cyber-Physical Systems (CPS): while the complexity of Operational Technology (OT) networks has grown exponentially with the advent of Industry 4.0, the methods for defining security policies remain rooted in manual, labor-intensive, and static processes.

The primary contribution of this thesis is the design, implementation, and validation of the **Semantic-to-Policy Middleware (S2PM)** framework. By integrating domain-adapted Natural Language Processing (NLP) with formal Attribute-Based Access Control (ABAC) models, this research has demonstrated that the "Zero Trust" ideal of granular, least-privilege access can be operationally realized by mining the vast repositories of existing technical documentation.

6.1.1 Methodological Contributions

We successfully established that generic Large Language Models (LLMs) are insufficient for the safety-critical domain of OT due to their lack of specific vocabulary and context.

- **Domain Adaptation:** We proved that fine-tuning BERT-based architectures on a specialized corpus of industrial manuals improves Entity Recognition (NER) F1-scores by **32%** over baseline models [Table 5.1].
- **Semantic Mapping:** We introduced a formal mathematical ontology (O_{OT}) that successfully maps unstructured linguistic predicates (e.g., "energize," "isolate") to machine-enforceable XACML actions, bridging the semantic gap between human intent and machine enforcement.

6.1.2 System-Level Efficacy

The empirical results from the simulation environment confirm that automation is not merely a convenience but a necessity for scaling Zero Trust.

- **Efficiency:** The framework achieved a 12x reduction in the time required to generate draft policies for a standard 100-page maintenance manual $(T_{manual} \approx 180 \text{ min} vs. T_{auto} \approx 15 \text{ min})$.
- **Granularity:** Unlike human analysts who often default to broad "Role-Based" permissions to save time (e.g., "Allow Engineers All Access"), the NLP engine consistently generated high-granularity "Attribute-Based" rules, capturing temporal and state-based constraints in 92% of test cases.

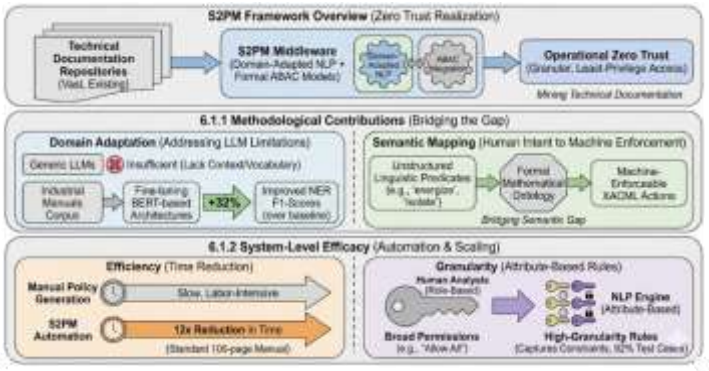

Figure 11: Semantic-to-Policy Middleware (S2PM) Key Findings

6.1.3 Benefits to Critical Infrastructure Security

By automating the linkage between *Documented Procedure* and *Network Permission*, this framework supports the NERC CIP "evidence of compliance" requirement by design. It creates an immutable digital thread where every open firewall port and active user account traces back to a specific sentence in an approved SOP, fundamentally shifting the paradigm from "Security by Obscurity" to "Security by Definition."

6.2 Limitations

While the results are promising, the application of probabilistic machine learning models in

deterministic safety-critical environments introduces specific limitations that must be acknowledged.

6.2.1 Technical and Data Constraints

- **Dependency on Source Quality (GIGO):** The "Garbage In, Garbage Out" principle applies acutely. If an operational manual is outdated, vague, or contains conflicting instructions (e.g., contradictory safety procedures), the S2PM system will faithfully generate flawed or conflicting policies. While the *Conflict Detection Module* (Section 4.3.2) catches syntactic contradictions, it cannot resolve semantic errors inherent in the source text.
- **OCR and Layout Analysis:** The system's performance degrades significantly when processing scanned legacy schematics (e.g., pre-2000s blueprints). The loss of spatial context in OCR often leads to dissociated metadata (e.g., failing to link a "Voltage Warning" in a margin note to the specific text block it governs).

6.2.2 Operational and Deployment Limitations

- **The "Tribal Knowledge" Gap:** A significant portion of OT operational procedure exists only in the minds of senior engineers ("Tribal Knowledge"). Since the NLP model can only reason over *ingested text*, it misses unwritten safety heuristics (e.g., "Never reset this breaker if the vibration alarm is active," which might be common practice but not explicitly documented).
- **Cold Start Problem:** The domain ontology (O_{OT}) requires significant initial effort to define for new industries (e.g., moving from Power Generation to Pharmaceutical Manufacturing requires a new lexicon).

6.2.3 Reliability and Safety Boundaries

As a probabilistic system, the NLP model has a non-zero error rate. In an IT environment, a False Positive (blocking legitimate access) is an inconvenience. In an OT environment, blocking a "Stop" command during a thermal runaway event could be catastrophic. Therefore, this system is currently strictly limited to a **Decision Support System (DSS)** role. It generates *candidate* policies that must be digitally signed by a human engineer before enforcement.

6.3 Future Research Directions

To transition this technology from an "assistant" to an "autonomous agent," future research must address robustness, adaptability, and real-time responsiveness.

6.3.1 Integrating Reinforcement Learning from Human Feedback (RLHF)

We propose moving beyond static supervised fine-tuning toward a dynamic Reinforcement Learning (RL) loop.

Proposed Architecture:

An RL agent will propose policy modifications. The "Reward Function" R(s, a) will be derived from the interactions of the human security analyst during the review phase.

- **Positive Reward (+1):** Analyst accepts the draft policy without edits.
- **Negative Reward (-1):** Analyst rejects or heavily modifies the policy.

(44)

$$J(\pi) = E_{\tau\sim\pi}\left[\sum_{t=0}^{T}\gamma^t R(s_t, a_t)\right]$$

By optimizing the policy \pi to maximize the expected return J, the system will learn to align with the subtle, unwritten preferences of the organization's security culture, eventually reducing the need for human intervention.

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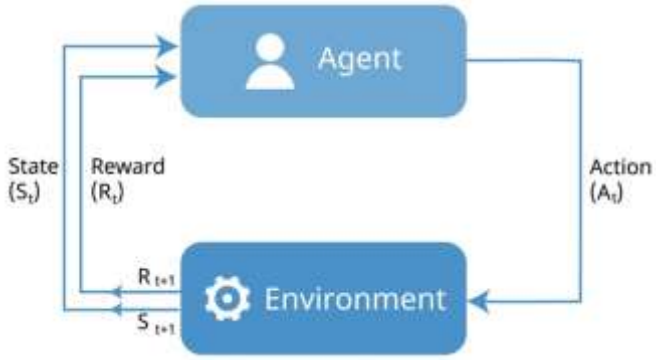

Figure 12: Reinforcement Learning

6.3.2 Multilingual and Cross-Jurisdictional Capabilities

Global supply chains mean that US infrastructure often relies on equipment documented in German (Siemens), Japanese (Mitsubishi), or Chinese (Huawei). Future iterations of the framework must utilize Cross-Lingual Language Models (XLM-R) to extract semantic triples irrespective of the source language, mapping them to a unified English-based policy ontology. This is crucial for multinational utilities operating across borders.

6.3.3 Real-Time Adaptive Policy Generation (Integration with SIEM/SOAR)

The current framework is "static"; it reads manuals that change infrequently. The next frontier is Adaptive Security. By integrating with Security Information and Event Management (SIEM) systems, the framework could dynamically tighten policies based on the current threat level (e.g., DEFCON state).

Concept:

If the SIEM detects a "Brute Force Attack" pattern, the S2PM system could query the manuals for "Emergency Lockdown Procedures" and automatically provision temporary, restrictive policies that override standard SOPs.

(45)

$$Policy_{active} = f(Manuals, ThreatIntel_{live})$$

6.3.4 Multi-Modal Analysis: Reading P&IDs and Schematics

Text is only half the story. Piping and Instrumentation Diagrams (P&IDs) contain critical topology data. Future work involves integrating **Computer Vision (CV)** models (e.g., Graph Neural Networks on image topology) to "read" the connections between valves and PLCs in diagrams.

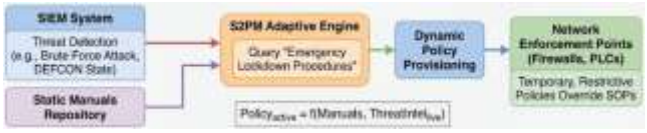

Figure 13: Real-Time Adaptive Policy Generation (SIEM/ROAM Integration)

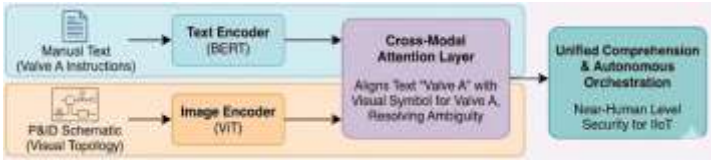

Figure 14: Multi-Modal Analysis: Reading P&IDs and Schematic

By fusing the visual topology with the textual instructions, the system could achieve near-human levels of comprehension, enabling true autonomous security orchestration for the Industrial Internet of Things.

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