

Intrusion Detection and Identification System Design and Performance Evaluation for Industrial SCADA Networks



Ahsan A.Z. Khan, Gursel Serpen*

Electrical Engineering and Computer Science Department, University of Toledo, Toledo, Ohio 43606, USA

Corresponding Author Email: gursel.serpen@utoledo.edu

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ABSTRACT

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Industrial SCADA networks are subject to cyber-attacks that have the potential to cause significant disruption, damage, and havoc. In this paper, we present a study that proposes a three-stage classifier model which employs a machine learning algorithm to develop an intrusion detection and identification system for tens of different types of attacks against industrial SCADA networks. The machine learning classifier is trained and tested on the data generated using the laboratory prototype of a gas pipeline SCADA network. The dataset consists of three attack groups and seven different attack classes or categories. The same dataset further provides signatures of 35 different types of attacks which are related to those seven attack classes. The study entailed the design of three-stage machine learning classifier as a misuse intrusion detection system to detect and identify specifically each of the 35 attack types. The first stage of the classifier decides if a record is associated with normal operation or an attack signature. If the record is found to belong to an attack signature, then in the second stage, it is classified into one of seven attack classes. Based on the identified attack class as determined by the output from the second stage classifier, the attack record is provided for a third stage attack type classification, where seven different classifiers are employed. The output from the third stage classifier identifies the attack type to which the record belongs. Simulation results indicate that designs exploring specialization to domains or executing the classification in multiple stages versus single-stage designs are promising for problems where there are tens of classes. Comparison with studies in the literature also indicated that the multi-stage classifier performed markedly better.

1. INTRODUCTION

Supervisory Control and Data Acquisition (SCADA) systems monitor and control highly critical industrial infrastructure. Such systems gather and analyze data, and control processes and systems all in real time for the most part. SCADA systems are used to monitor and control a plant or equipment such as gas pipeline, water storage tank and associated distribution network, telecommunications, waste control, oil refining and transportation among many others. A SCADA system may collect information such as where a leak on a gas pipeline has occurred; alert the central control room that leak has occurred; and carry out necessary analysis and control (such as determining if the leak is critical or not). A SCADA system can be very simple i.e., just monitoring environment of a small manufacturing facility or it can be very complex such as monitoring activity of an oil refinery or a nuclear power plant.

Computers were first used for industrial control purposes as early as late 1950s [1]. Telemetry was established for monitoring in the 1960s, which allowed for automated communications to transmit measurements. In the early 1970s, the term “SCADA” was coined and the rise of microprocessors and programmable logic controllers (PLCs) during that decade increased enterprises’ ability to monitor and control automated processes more than ever before. SCADA systems have undergone significant changes in subsequent decades. During

late 1990s to early 2000s, a technological revolution occurred as computing and information technologies (IT) accelerated in growth. The introduction of modern IT standards and practices such as Structured Query Language (SQL) and web-based applications for SCADA networks has improved the efficiency and productivity overall. Many SCADA systems are either online or able to connect to other similar systems or both, and with this newfound connectivity, there are also many security concerns for these once remote, isolated and standalone systems [2]. If a vulnerability exists in one of these systems, it will now allow attackers to remotely exploit and potentially be able to take control of these SCADA systems; the stakes then could not be higher as takeover by a bad actor could lead to unimaginable and catastrophic consequences. Table 1 provides some common SCADA attack scenarios. Hong et al. discuss inherent security issues in SCADA systems for smart grid communications [3]. Similar to this work, Dzung et al. outlines many issues found in communication networks for industrial applications [4]. Mirian et al. [5] found out that 60,000 vulnerable SCADA devices were connected to the Internet using the scanner called Zmap [6]. A detailed survey of risk assessment studies reported in the literature for industrial SCADA systems is presented by Cherdantseva et al. [7].

An intrusion detection system (IDS) is a special-purpose computing platform or software application that monitors a network or systems for unauthorized access, control or

malicious activity. Intrusion detection systems are used to collect data and analyze system activity to monitor a system's status and state [8]. Many IDSs use machine learning algorithms for pattern recognition to detect and identify any threat activity. There are mainly two types of IDSs. One type uses a signature-based approach to compare activity to a database of known threats, and as such are considered to perform misuse detection. The other type can identify an operation mode of the system as outside the boundaries of normal mode, which is then characterized as performing anomaly detection. These functionalities can be combined for a robust detection system and will likely form a baseline design for minimally adequate layer of protection against attacks.

Table 1. Common SCADA system threats [2]

Sabotage	Scavenging	Spying	Spoofing
Worm	Access Violation	Trojan Horse	Tunneling
Information Leakage	Data Modification	Physical Intrusion	Resource Exhaustion
Eavesdropping	Repudiation	Intercept Traffic	Terrorism
Substitution	Theft	Analysis	Virus

The highly critical operational nature of SCADA systems mandates using Intrusion Detection Systems for defense against attacks exploiting vulnerabilities in those systems. A recent study [9] used real world data from an industrial system (water plant) to experiment with two different approaches. The research concludes with a finding that behavioral approach for intrusion detection can help yield high detection rates for SCADA networks. Feng et al. proposed a deep learning-based framework to detect attacks against SCADA networks in industrial systems [10]. Their framework shows that Artificial Intelligence (AI) can be helpful to detect even stealthy attacks on SCADA systems given that such attacks are normally very hard to detect. Several other industrial control system specific anomaly and intrusion detection system models have been reported in the studies [11-13]. Perez et al. [14] used Random Forest to build an IDS and classify attacks against a SCADA system for a gas pipeline. Shirazi et al. [15] proposed one-class classification using support vector machines (SVM). Demertzis et al. [16] proposed a one-class anomaly detection system for industrial control systems. Anton et al. proposed anomaly-based intrusion detection with industrial data with both SVM and Random Forest [17].

Current industrial SCADA networks are facing constantly evolving threats from hackers with potentially catastrophic consequences for mission-critical tasks. The defensive tools must be also in a state of evolution to address these ever-changing threats. New vulnerabilities are being exploited by the adversaries of such systems, which requires a constant engagement in terms of engineering such systems for defense. Therefore, there is an ongoing and urgent need to continue with the development of intrusion detection systems to counter the existing or future threats being posed to such systems. Consequently, the research presented in this study strives to fill this need for the constant evolution of IDSs considering continuously evolving threats.

SCADA networks for industrial infrastructure employ networking protocols to facilitate communication for command and control. There is much information embedded in the networking packets which can be leveraged for intrusion

detection purposes. This requires collection of data to be used for development of data-driven decision-making tools such as machine learning classifiers. The significant and substantial differences in the design and architecture of SCADA networks for different industrial settings poses a hindrance to development efforts as an intrusion detection system developed for a water distribution system cannot be readily adopted for an oil refinery, gas pipeline or industrial manufacturing plant [18].

The study presented in this paper entails a SCADA system for a gas pipeline for which public domain dataset for the development of intrusion detection system is available [18]. Other studies reported in the literature and using the same dataset suggest that there is a further need to develop an IDS that can detect and identify one of 35 attack types with high accuracy [14-16, 19-27] as this is currently an unresolved problem. Anthi et al. [19] employed a three-tiered intrusion detection system to detect attacks (vs. non-attacks), attack classes, and specific type of attacks. They reported good performance for the first two cases but relatively poor performance for the case where one out of 35 attack types need to be identified reliably. Several other studies considered the classification problem for seven classes only. Demertzis et al. [16] proposed one-class anomaly detection approach for this dataset. Apart from being an anomaly (versus misuse) detection system, their study exposes several important differences when compared to ours. One significant difference is that they did not employ the full dataset in their study. They subsampled 97,019 instances from 274,628 instances in the original dataset. Considering this, one can question if the two studies are directly comparable. Perez et al. [14] reported better performance than that of the current study. However, their approach employed 80-20% ratio for splitting the dataset into training and testing subsets, which is not the same as the 67-33% split ratio for the dataset where the latter is typical for most studies including the current one. A different split ratio through subsampling the data could change the original signatures of attacks which could lead to differences in classification performance. For the study [15], performance results are demonstrably not promising. Nguyen et al. [20] leveraged a stacking ensemble of tree-based models for classification. They studied the binary classification (attack vs. non-attack), and the 7-category classification: they reported good performance but did not address the case of identifying the specific attack type. Nazir et al. [21] approached the problem from the perspective of anomaly detection: they considered the seven-category classification problem only. Many other studies on this dataset only considered the binary classification problem [22-28].

There are two main and interrelated objectives of the research study presented in this paper. First such objective is to explore the information content of networking packets for communication and command in SCADA networks to determine the feasibility of identification of detected attacks at a multitude of levels as a) Detection of attacks occurring versus normal operation; b) Detection and identification of a specific attack class group where a group consists of several attacks sharing common attributes; and c) Detection and identification of a specific type of attack occurring in a context where there are tens of such attacks can occur, which has not received requisite attention from the researchers to date. The second objective is to explore the performance of a multi-stage classifier architecture design.

The simulation study demonstrated that the proposed 3-

stage classifier design performed very well. Stage 1 binary classifier had 98.16% accuracy for the case of attack vs. normal; Stage 2 classifier was able to identify the attack class for 5 out of 7 classes with high accuracy; and finally Stage 3 classifier identified 28 out of 35 attack types also with high accuracy.

We present the dataset and the preprocessing of data in Section 2. Classifier design is presented in Section 3. Simulation study, and its results along with comparison with other studies reported in the literature are presented in Section 4. The last section presents the conclusions.

2. DATASET DESCRIPTION, PREPROCESSING AND TRAINING-TESTING PARTITIONING

This section presents the Gas Pipeline dataset [12], its features and attack class labels. It also presents the preprocessing steps and methods applied to the datasets to fill in the missing values.

2.1 Dataset features

The original dataset has 17 features and 3 different class label groups namely binary, categorized and specified. There are a total 274,628 instances in the dataset. There are 11 Command Payload features which are related to the command injection attacks, 5 Network features, and 1 Response Payload feature related to the response injection attacks as listed in Table 2. We next provide a brief description for each of the twenty features in Table 2. The detailed description of features and the associated collection method can be found in Turnipseed [18].

The station address feature is a unique eight-bit value assigned to each master and slave device. In broadcast mode, all slaves receive the transmitted frame and need to check the address field to determine if it is the intended recipient. This feature is useful for the detection of scan attacks. Up to 256 different function codes such as read and write commands can be executed in the system and this information is contained by the second feature. One typical attack leveraging this feature is the denial of service by forcing a slave to the listen-only mode. Modbus frame length which is fixed for command and response queries is contained by the third feature. A frame with a different length can easily be detected as not normal. Another feature indicates the set point value for controlling the pressure in the pipeline in automatic mode. Manipulation of this value by an attacker could cause major damage to the system. PID controller values such as gain, reset rate, dead band, cycle time, and rate are represented by five other features. The system’s duty cycle with three possible values is controlled and represented by another feature. System control through the pump or the solenoid is accomplished by the so-called control scheme which is contained by the eleventh feature. In the event the system mode is manual, the state of the pump, namely either off or on, is controlled by a dedicated field in the frame constituting the twelfth feature. The state of solenoid valve as either open or closed is controlled a dedicated field in the frame: the thirteenth feature contains this information. Tampering with the state of either the pump or the solenoid could cause serious damage. The current pressure measurement for the pipeline is contained by the fourteenth feature. The cyclic redundancy check data which facilitates checking for errors in a frame is contained by the fifteenth

feature. An additional feature is included to distinguish between commands and responses. The last four features specify the time stamp, attack type, attack class, and attack vs. normal data.

2.2 Description of attacks

The gas pipeline dataset used in this study has 7 types or categories of attacks as presented in Table 3. The description for all attack types is given in Morris and Gao [12]. Naïve Malicious Response Injection (NMRI) and Complex Malicious Response Injection (CMRI) are the response injection attacks. These attacks can hide by mimicking certain behaviors which occur within normal operating bounds. This makes them very difficult to detect, and hence giving the appearance of the system operating normally. NMRI has out of bounds behavior that would not be present in normal operation. It typically occurs when the attacker lacks information about the physical system process. CMRI attacks provide a level of sophistication over NMRI attacks. These attacks can change the state of a system which can be seen as command injection attacks: they are difficult to detect.

Table 2. Original features in gas pipeline dataset [18]

Features	Type	Values
Address	Network	Numeric
Length	Network	Numeric
Gain	Command Payload	Numeric
Deadband	Command Payload	Numeric
Rate	Command Payload	Numeric
Control Scheme	Command Payload	0 or 1
Solenoid	Command Payload	0 or 1
CRC Rate	Network	Numeric
Function	Command Payload	Numeric
Set Point	Command Payload	Numeric
Reset Rate	Command Payload	Numeric
Cycle Time	Command Payload	Numeric
System Mode	Command Payload	0 or 1 or 2
Pump Mode	Command Payload	0 or 1
Pressure Measurement	Response Payload	Numeric
Command Response	Network	0 or 1
Timestamp	Network	UNIX format
Binary Attacks	Label	0 or 1
Categorized Attacks	Label	0, 1, 2...,7
Specified Attacks	Label	0, 1, 2..., 35

Table 3. Attack classes in gas pipeline dataset

Attack Type/Category/Class Name	Acronym	Instances
Normal	n/a	214580
Naïve Malicious Response Injection	NMRI	7753
Complex Malicious Response Injection	CMRI	13035
Malicious State Command Injection	MSCI	7900
Malicious Parameter Command Injection	MPCI	20412
Malicious Function Code Injection	MFCI	4898
Denial of Service	DoS	2176
Reconnaissance	Recon	3874

Malicious State Command Injection (MSCI), Malicious Parameter Command Injection (MPCI), and Malicious Function Code Injection (MFCI) labels belong to the command injection attacks. Tables 4 and 5 show their specific attack types and their adverse impact on the system. Much damage may originate from command injections attacks: interruption in device communications, modification of device configuration, and modification of the PID values are some of

them. MSCI attacks modify the state of the current physical process of the system and can potentially place the system into a critical state. Table 4 specifies the MPCCI attack types. It mainly modifies the parameters of PID configurations and set point. As listed in Table 5, MFCI attacks inject commands which exploit the network protocol for restarting, cleaning registers etc.

Table 4. MPCCI attack subtypes

Attack Name	Attack Type No	Class	Description
Setpoint Attacks	1-2	MPCCI	Changes the pressure set point outside and inside of the range of normal operation.
PID Gain Attacks	3-4	MPCCI	Changes the gain outside and inside of the range of normal operation.
PID Reset Rate Attacks	5-6	MPCCI	Changes the reset rate outside and inside of the range of normal operation.
PID Rate Attacks	7-8	MPCCI	Changes the rate outside and inside of the range of normal operation.
PID Deadband Attacks	9-10	MPCCI	Changes the dead band outside and inside of the range of normal operation.
PID Cycle Time Attacks	11-12	MPCCI	Changes the cycle time outside and inside of the range of normal operation.

Table 5. MSCI, MFCI, DoS, recon attack subtypes

Attack Name	Attack Type No	Class	Description
Pump Attack	13	MSCI	Randomly changes the state of the pump.
Solenoid Attack	14	MSCI	Randomly changes the state of the solenoid.
System Mode Attack	15	MSCI	Randomly changes the system mode.
Critical Condition Attacks	16-17	MSCI	Places the system in a Critical Condition. This condition is not included in normal activity.
Bad CRC Attack	18	DoS	Sends Modbus packets with incorrect CRC values. This can cause denial of service.
Clean Register Attack	19	MFCI	Cleans registers in the slave device.
Device Scan Attack	20	Recon	Scans for all possible devices controlled by the master.
Force Listen Attack	21	MFCI	Forces the slave to only listen.
Restart Attack	22	MFCI	Restarts communication on the device.
Read ID Attack	23	Recon	Reads ID of slave device.
Function Code Scan Attack	24	Recon	Scans for possible functions that are being used on the system.

Denial of service (DoS) attacks are very common in almost every networked and online system. In a SCADA system, a DoS attack attempts to disrupt communication between the control or monitoring system and the process. Another category of attacks are reconnaissance attacks. These attacks aim to collect information about the system through some passive activity. They may also query the device for

information such as function codes, model numbers etc. Specific attack types belonging to NMRI or CMRI are listed in Table 6.

2.3 Preprocessing

In the preprocessing stage, missing values in the dataset were filled in. There were missing values in the dataset for 11 Payload (10 Command Payload and 1 Response Payload) features. The missing values could have been imputed in multiple ways. For instance, Perez et al. [14] have imputed the missing values in 4 different ways such as mean value, keeping previous value, zero imputation, and K-means imputation for the same dataset. In the gas pipeline dataset, missing values were occurring as MAR (Missing at Random) or NMAR (Not Missing at Random). The payload features were not occurring at random as the solenoid or pump mode values were fixed among 0,1 or on/off/automatic. But the pressure measurement value was occurring randomly while an associated attack was in progress. Accordingly, the missing values were imputed with Multivariate Imputation by Chained Equation (MICE) method [29] since the MICE algorithm can handle both MAR and NMAR types. This type of imputation works by filling the missing data multiple times. Multiple Imputations are much better than a single imputation as it measures the uncertainty of the missing values more precisely [29]. The chained equations approach is also very flexible and can handle different variables or different data types.

Table 6. NMRI & CMRI attack subtypes

Attack Name	Attack Type No	Class	Description
Rise/Fall Attacks	25-26	CMRI	Sends back pressure readings which create trends.
Slope Attacks	27-28	CMRI	Changes pressure reading by a random slope
Random Value Attacks	29-31	NMRI	Random pressure measurements are sent to the master.
Negative Pressure Attacks	32	NMRI	Sends back a negative pressure reading from the slave.
Fast Attacks	33-34	CMRI	Sends back a high set point then a low setpoint which changes "fast"
Slow Attack	35	CMRI	Sends back a high setpoint then a low setpoint which changes "slowly"

2.4 Dataset partitioning for training and testing

To create the train-test data subsets, we partitioned the original dataset into three splits and then formed training-testing datasets at a ratio of 66.6% and 33.3% and repeated three times to form three data folds. The original dataset was split into three equal parts while preserving class representations equally in each split. Each fold contains two splits for training and the third split is used for testing: this procedure generates a unique split for testing for a given fold.

3. CLASSIFIER DESIGN

The design of the 3-stage machine learning classifier is illustrated in Figure 1. The classification algorithm for all three stages is chosen as Random Forest [30] given its superior performance as presented in a previous publication by Khan

[31]. The first stage classifier performs binary classification outputting if the class is normal or attack. If the classification output is normal, then no further action is taken. However, if the classification output is attack, then second stage classifier is activated. The pattern that was classified as attack by the first stage binary classifier is input to the second stage classifier. The second stage classifier performs attack class identification on the input pattern that was classified as an attack (vs. normal) by the first stage binary classifier. There are 7 class labels or outputs from the second stage classifier corresponding to 7 attack classes. Once the class label is identified by the second stage classifier the corresponding third stage classifier is activated to perform attack type identification. There are 7 attack type classifiers performing this task in the third stage: six of the seven are implemented noting that there is only one type for the DoS attack class.

4. SIMULATION STUDY

Simulation study was performed to determine the performance of the 3-stage classifier on each of the three folds. Performance assessment and evaluation was done separately for each test data split and further inferences were made based on these three performance assessments and evaluations.

Training the 3-stage classifier was accomplished by implementing the following procedure:

- Step 1: Train the binary classifier in Stage 1 with two class labels of Normal versus Attack.
- Step 2: Remove all patterns with class label “Normal” and replace the single “Attack” label with 7 attack class labels in the training dataset.
- Step 3: Train the 7-category classifier in Stage 2 with training dataset modified as in step 2.
- Step 4: Split the single training dataset as modified in step 2 into 7 subsets (one for each attack class); replace, in each training subset, class labels with the corresponding attack type labels. A training data subset will have those records or instances belonging to specific attack types of a given attack class.
- Step 5: Train each of the 7 classifiers in Stage 3 using corresponding training data subsets modified in step 4.

Performance assessment and evaluation was done by implementing the following procedure:

- Step 1: Classify the pattern in the testing data subset with binary class labels using Stage 1 classifier.
 - If classification output is “Normal” then no further processing is needed.
 - Else (classification must be “Attack”) continue with Stage 2 processing.
- Step 2: Classify the attack pattern into one of seven classes in the testing data subset using the 7-category classifier in stage 2. Based on the output from the single 7-category classifier, chose the Stage 3 classifier among 7 to activate.
- Step 3: Classify the attack pattern in the testing data subset using the attack type classifier (among those 7 at stage 3) as identified in Stage 2.

4.1 Simulation results and discussion

Weka classifier Random Forest was used for all classifier models in all 3 stages [31]. The training set of the first data fold contains dataset splits 1 and 2 while the dataset split 3 is

employed as the test set. Table 7 presents the number of instances available in both training and testing data subsets for stage 1. We report the representative results for one of the three data folds since results for all three folds are very similar to each other with negligible differences.

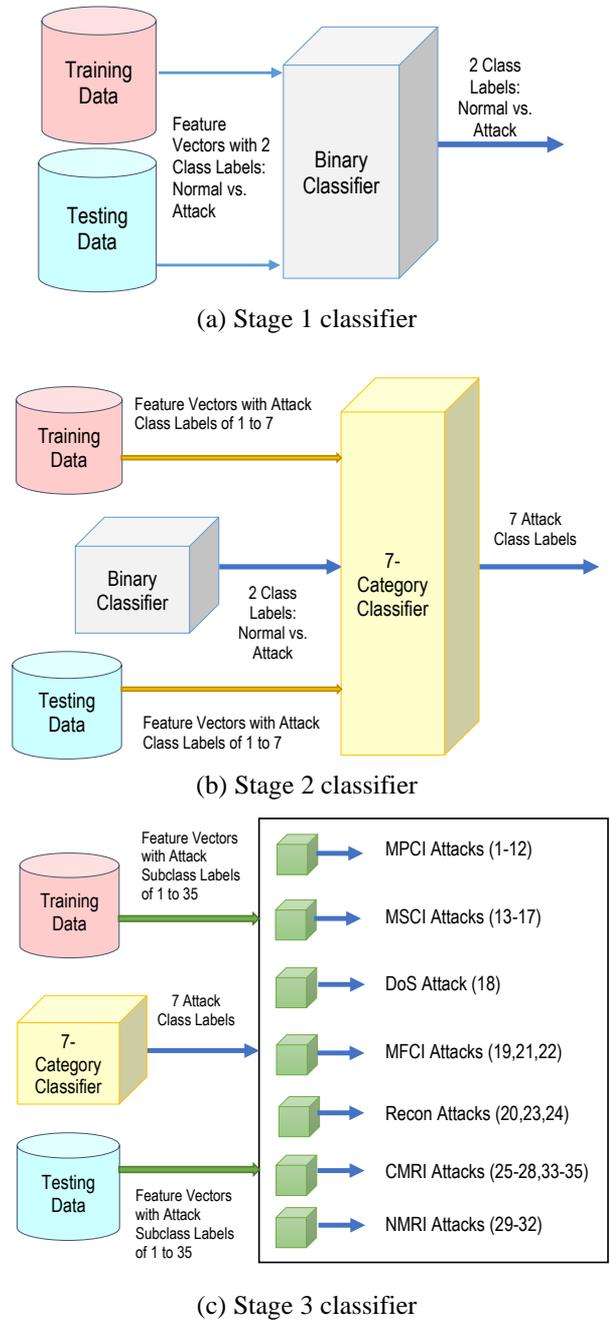


Figure 1. 3-stage classifier design

Table 7. Instance counts for stage 1

	Classes		
Dataset	Normal	Attack	Total
Training	142901	40138	183039
Testing	71679	19910	91589

For stage 1, the batch size is 1000 for the Random Forest model which classified 89,906 instances correctly from the test set yielding 98.16% accuracy. The confusion matrix in Table 8 shows 18,597 attack instances were classified correctly among the 19,910 and thus resulting in 1,313 incorrectly

classified attack instances. From Table 9, we see that false negative rate (FNR) for the attack class is 6.6% which corresponds to the 1,313 incorrectly classified attack instances.

Table 8. Stage 1 confusion matrix

Classified as →	Normal	Attack
Normal	71309	370
Attack	1313	18597

Table 9. Stage 1 performance (accuracy = 98.16%)

Class	TPR	FPR	TNR	FNR	Precision	Recall
Normal	0.995	0.066	0.934	0.005	0.982	0.995
Attack	0.934	0.005	0.955	0.066	0.980	0.934
Weighted	0.982	0.053	0.947	0.018	0.982	0.982

Next, the training set is modified: all 142,901 normal class patterns are removed from the training set of stage 1. This leaves only the attack class instances in the training set for stage 2. Table 10 presents the number of instances available in training and testing data subsets for stage 2.

Table 10. Instance counts for stage 2

	Class Label							
	1	2	3	4	5	6	7	Total
Training	5222	8743	5361	13550	3232	1449	2581	40138
Testing	2531	4292	2539	6862	1666	727	1293	19910

The batch size used for stage 2 classification is 100 as the number of instances decreased in comparison to stage 1. Random Forest at Stage 2 classifies with 93.79% accuracy where 18,674 test instances are correctly classified and 1,236 are incorrectly classified. The weighted FNR is 6.2% for stage 2. From the confusion matrix in Table 11 we see that the model struggles distinguishing mainly between attack classes 1 and 2. There are 1161 incorrectly classified instances between attack classes 1 and 2 which amounts to approximately 94% of incorrectly classified instances. NMRI and CMRI, being both response injection attacks, deal with mainly the pressure measurement features which have overlapping values for both attack classes 1 and 2. For example, both attacks have same pressure values in the range of 2 to 10 kPa. That is the most likely reason why the classifier struggles to distinguish between them. This finding also indicates the need to determine and formulate new features which would be discriminatory between attack classes 1 and 2.

Performance metric values for the stage 2 classifier are presented in Table 12. The accuracy is 93.79% for the classifier. Lower values for all the metrics for classes 1 and 2 reinforce the findings drawn from the confusion matrix that the design needs to be enhanced to be able to better distinguish between attack classes 1 and 2.

Table 11. Stage 2 confusion matrix

Classified as →	1	2	3	4	5	6	7
1	1881	650	0	0	0	0	0
2	511	3781	0	0	0	0	0
3	0	0	2522	15	0	2	0
4	0	0	22	6835	0	5	0
5	0	0	0	0	1666	0	0
6	0	0	6	15	0	706	0
7	0	0	0	0	10	0	1283

In stage 3, seven classifiers are used. Training and testing datasets of stage 2 are now divided into 7 separate training and testing subsets. Each of the 7 training and testing data subset pairs have associated subclass labels, which range from 1 to 35, belonging to corresponding stage 2 class labels. Table 13 presents the number of instances available in both training and testing data subsets for stage 3 classifiers.

Table 12. Stage 2 performance (accuracy = 93.79%)

Class	TP Rate	FP Rate	TN Rate	FN Rate	Precision	Recall
1	0.743	0.029	0.971	0.257	0.743	0.764
2	0.881	0.042	0.958	0.190	0.853	0.881
3	0.993	0.002	0.998	0.007	0.989	0.993
4	0.996	0.002	0.998	0.004	0.996	0.996
5	1.000	0.001	0.999	0.000	0.994	1.000
6	0.971	0.000	1.000	0.029	0.990	0.971
7	0.992	0.000	1.000	0.008	1.000	0.992
Weighted	0.938	0.014	0.986	0.062	0.937	0.938

In stage 3, the batch size is 10 for the Random Forest classifier as the test data subset size is further reduced following the processing as a result of classification during stage 2. Since the attack class 6 (DoS) has only 1 specified subclass (18) in the dataset, it was not necessary to build a classifier for it. Tables 14 through 19 present the confusion matrices for all 6 other subclass classifiers.

Table 13. Instance counts for stage 3

Stage 2 Label	Stage 3 Label	Training Count	Testing Count
4	1	1221	571
	2	1015	445
	3	1126	574
	4	1277	655
	5	931	485
	6	1326	700
	7	997	515
	8	1186	612
	9	936	460
	10	955	519
	11	1206	628
	12	1374	698
3	13	1077	517
	14	1158	518
	15	1148	510
	16	1115	543
	17	963	451
6	18	1449	727
5	19	1089	545
7	20	474	192
5	21	1134	588
	22	1009	533
7	23	1355	693
	24	752	408
2	25	995	477
	26	1237	571
	27	1389	690
	28	1233	625
	29	1276	580
	30	1414	706
	31	1268	638
1	32	1264	607
	33	1071	533
	34	1327	683
	35	1491	713

For class label 1, the confusion matrix is presented in Table 14: the classifier struggles to distinguish between attack subclasses 31 and 32. Attack subclass 31 is dependent on the random pressure measurements sent to the device and attack subclass 32 is dependent on the negative pressure readings sent to the device. The classifier fails to detect these two attacks whenever the random pressure sent to the device is also negative and detects 31 as 32 or 32 as 31. Additionally, subclass 29 also has relatively poor detection rates as it is misclassified as subclass 31 or 32 while a good number of patterns belonging to attack subclasses 31 or 32 are also classified as 29. The classifier for attack class 1 achieves an accuracy rate of only 82.30%. The FNR is 17.7%, which is very high compared to other classifiers for the same metric. Performance of classifier for attack class 2, presented in Table 15, is the second worst with 87.79% accuracy and 524 incorrectly classified instances. All other classifiers performed at a much higher level, specifically 99% or better as shown in Tables 16 through 20.

Table 14. Stage 3 class label 1 confusion matrix

Classified as →	29	30	31	32
29	400	7	86	87
30	0	706	0	0
31	52	0	527	59
32	74	0	83	450

Table 15. Stage 3 class label 2 confusion matrix

Classified as →	29	30	31	32	33	34	35
25	368	41	3	42	2	4	17
26	37	479	0	45	0	4	6
27	2	0	671	1	2	0	14
28	35	74	3	423	51	13	26
33	0	0	7	6	505	0	15
34	0	0	7	2	0	647	27
35	1	0	7	3	10	17	675

Table 16. Stage 3 class label 3 confusion matrix

Classified as →	13	14	15	16	17
13	513	1	1	0	2
14	0	516	1	0	1
15	1	1	506	1	1
16	0	1	1	540	1
17	0	2	1	0	448

4.2 Comparison with studies reported in literature

Table 17. Stage 3 class label 4 confusion matrix

	Classified as											
	1	2	3	4	5	6	7	8	9	10	11	12
1	569	1	0	0	0	0	0	0	1	0	0	0
2	1	431	0	0	0	6	0	0	1	6	0	0
3	0	0	573	1	0	0	0	0	0	0	0	0
4	0	0	0	655	0	0	0	0	0	0	0	0
5	0	0	0	0	481	2	0	1	0	0	0	1
6	1	2	0	0	0	692	0	0	0	5	0	0
7	1	0	0	1	0	0	512	0	1	0	0	0
8	0	0	0	0	2	0	0	609	0	1	0	0
9	0	0	0	1	0	0	0	0	458	1	0	0
10	0	1	0	0	0	0	1	0	2	515	0	0
11	0	1	1	2	0	0	0	0	0	0	624	0
12	0	0	0	0	0	1	0	1	0	0	0	696

Numerous studies using the same gas pipeline dataset were reported in the literature: several of them only reported the binary classification results [22-27] while others considered the classification problem for seven attack classes as presented in Table 21 [14-16, 19-21]. Many appear to employ at least one aspect of data preprocessing, classifier design and testing that could render the comparison with the design proposed in this study not very meaningful or even valid. Nevertheless, for the sake of establishing somewhat meaningful context for the performance of the proposed design, we briefly discuss each one next. For a comparison with the other studies in the literature on the same dataset, it is then necessary to calculate the combined performance of stages 1 and 2 for the design proposed in this study. The accuracy of combined stages 1 and 2 is $0.9379 \times 0.9806 = 92.06\%$. Precision and recall rates are $0.937 \times 0.982 = 0.920$ and $0.938 \times 0.982 = 0.921$, respectively.

Table 18. Stage 3 class label 5 confusion matrix

Classified as →	19	21	22
19	544	1	0
21	0	588	0
22	0	0	533

Table 19. Stage 3 class label 7 confusion matrix

Classified as →	20	23	24
20	187	0	5
23	0	693	0
22	2	0	406

Table 20. Stage 3 performance

Classifier	Accuracy	TPR	FPR	TNR	FNR	Precision	Recall
1	82.30%	0.823	0.057	0.943	0.177	0.822	0.823
2	87.79%	0.878	0.020	0.980	0.202	0.876	0.878
3	99.37%	0.994	0.002	0.998	0.006	0.994	0.994
4	99.32%	0.993	0.001	0.999	0.007	0.993	0.993
5	99.94%	0.999	0.000	1.000	0.001	0.999	0.999
6	100.00%	1.000	0.000	1.000	0.000	1.000	1.000
7	99.47%	0.995	0.002	0.998	0.005	0.995	0.995

Demertzis et al. [16] and Nazir et al. [21] proposed one-class anomaly detection approach where the former as also reported subsampling the dataset. Perez et al. [14] reports better performance compared with that of the current study, and yet their approach employed 80-20% ratio for splitting the dataset into training and testing subsets. Results reported in the studies [15, 19] suggest poor performance across all the metrics considered.

Table 21. Performance comparison of 2-stage classifier with studies in literature

Classifier	Accuracy	Precision	Recall
This Study	92.06%	0.920	0.921
Random Forest [14]	99.41%	0.994	0.994
K-Means [15]	56.80%	0.832	0.573
GMM [15]	45.16%	0.731	0.442
OCC-eSNN [16]	98.82%	0.988	0.988
OCC-SVM [16]	97.98%	0.980	0.980
C4.5/J48 [19]	76.57%	0.780	0.760
Ensemble [20]	99.62%	0.996	0.996

The only other cited study which attempted to address the classification problem for the case of 35 attack types through

a 3-stage design reported precision, recall and f-measure values of 0.586, 0.434, and 0.445, respectively [24]. Comparing these performance metric values with those in Table 20 shows that the 3-stage design proposed in our study performed very well.

5. CONCLUSIONS

In this study, we proposed a three-stage classifier for detecting and identifying known intrusions for a gas pipeline-based SCADA network. The dataset, which was developed using an academic laboratory setup at the Mississippi State University, entails 3 attack groups, 7 attack classes and 35 attack subclasses or types. Random Forest classifier was used for all stages. Simulation results showed that 24 out of 35 attack subclasses or types, which belonged to attack classes 3, 4, 5, 6, and 7, were detected and identified with relatively high accuracy while the performance for the remaining 11 attack subclasses, which were associated with attack classes 1 and 2, was not at par as it lagged by a considerable margin. Given that the studies in literature which attempt to detect and identify at the level of tens of attack subclasses or types are scarce at best, the proposed and novel three-stage classifier model in this study is promising for its overall performance to address those types of problems.

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