#### جامعـة نيويورك أبـوظـبي NYU ABU DHABI



# Remote Non-Intrusive Malware Detection for PLCs based on Chain of Trust Rooted in Hardware

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MMA

### Industry 4.0

And its security aspects

- Improves industry output by integrating IoT with OT.
- ICS constraints
- Limited computational capabilities
- Realtime requirements
- Limited OS support



### Contributions

Research question

Is it possible to detect malware on an ICS device non-intrusively without disrupting industry operation, in real-time?

### ORRIS

- Novel methodology for JTAG-based non-intrusive PLC monitoring for malware
- ORRIS evaluation using spatial bias and unseen malware samples
- End-to-end case-study of desalination plant using ORRIS
- Development of an ARM-based malware dataset



### Threat model

Chain of trust established by ORRIS



- Adversary can obtain elevated privileges
- Can exploit vulnerabilities in the PLC OS
- JTAG establishes a hardware root of trust
- Hardware -> Kernel space -> User space



# **Designing ORRIS**

#### **Kernel-level rootkits**

- Protection against rootkit that alter static kernel data structures
- Set watchpoint over syscall table
- Monitor for any write operation over the table (watchpoint)

#### **User-level rootkits**

- Hook to write syscall
- Monitor writes on /etc/ld.so.preload
- Get file path and use static features for detection

#### Malware

- Extract semantic and microarchitectural event counts
- Check the overall state of the PLC



### Malware detection methodology

- Feature collection with JTAG
- Balancing sampling rate for performance and responsiveness

#### **Pre-processing of malware dataset**

- <u>Manual scrubbing</u>: Remove constants, static identifiers, zeroes, process identifiers, and memory addresses
- <u>Statistical</u>: Standard scaling with 99.75% accuracy

#### Machine learning based models

- MI between output labels and features reduces the feature set by 39.
- OCSVM -> user-level rootkit
- SVM -> malware (99.75%)





# Evaluation of ORRIS (1/2)

Testing rootkit detection and real-time implementation

#### **Kernel-level Rootkits**

• Detected all the 11 tested kernel-level rootkits

#### **User-level Rootkits**

- 4 rootkits vs. 425 shared libraries
- Accuracy of 96.3% with TNR of 96.2%
- 3.8% shared libraries are misclassified
- Hardware-in-the-Loop simulation of MSF desalination plant
- ORRIS on a Test PLC that closes a steam flow valve at high brine temperature
- No observed delay on control logic execution



Fig. 5: Outlier detection for user-level rootkits





## Evaluation of ORRIS (2/2)

Testing spatial bias and unseen malware



- Increased ratio of goodware to malware
- Moving window average accuracy stays between 98% and 100% (window size: 5)

Table 1: Re	asons for	accuracy	decrease
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Drift Point	Reason	Malware
A	Limited training on test malware variant	Mirai.N
В	New malware variants	Dofloo.D, Mirai.Au, Gafgyt.Az, Gafgyt.Ak, Mirai.Ax, Gafgyt.Aj, Dofloo.F and Tsunami.Bh
	New malware	Mirai.B and DnsAmp.C
C	New malware variant	Tsunami.Br
D	Limited training on test malware variants	Tsunami.Bh and Mirai.Au



### Discussion and conclusion

### Limitations

- JTAG is slow
- Sometimes not enabled by default
- Scalability

### ORRIS

- Out-of-the device
- Non-intrusive
- Malware detector (user-level and kernel-level)







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#### Github

github.com/momalab/orris

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