

# Leveraging Secure Multiparty Computation in the Internet of Things

#### Marcel von Maltitz, Georg Carle

Tuesday 12th June, 2018

Chair of Network Architectures and Services Department of Informatics Technical University of Munich





#### Smart Buildings - Industrial State of the Art

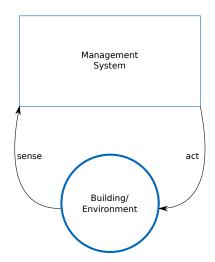




https://www.siemens.com/innovation/en/home/pictures-of-the-future/infrastructure-and-finance/smart-cities-smart-buildings.html Marcel von Maltitz and Georg Carle — Leveraging Secure Multiparty Computation in the Internet of Things

# Smart Buildings: Model





### Smart Buildings - Industrial State of the Art

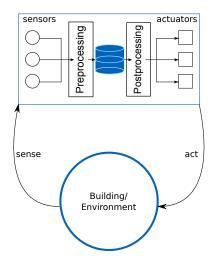




https://www.ge.com/digital/predix-platform-foundation-digital-industrial-applications

### Smart Buildings: Model





# Smart Buildings: Privacy Criticality

#### Types of Sensors

- Brightness
- Temperature / Humidity
- CO<sub>2</sub> concentration
- Motion
- Weight (on floor)
- Device usage
- Power consumption

• ...

#### Privacy-criticality

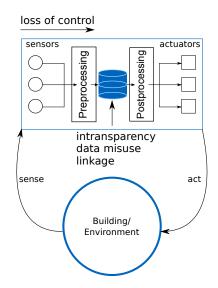
- Location
- Behavioral patterns (cf. [8])

#### Threats (cf. [5])

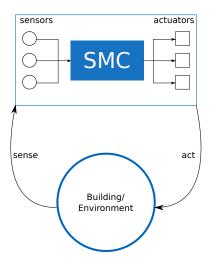
- Intransparency of data usage
- Data misuse (other purpose)
- linkage (combination of data for more insights)
- Loss of control (data subjects)

### Smart Buildings: Privacy Criticality





### Smart Buildings: Application for Secure Multiparty Computation



Marcel von Maltitz and Georg Carle — Leveraging Secure Multiparty Computation in the Internet of Things

1Ш



9

#### Definition (cf. [6])

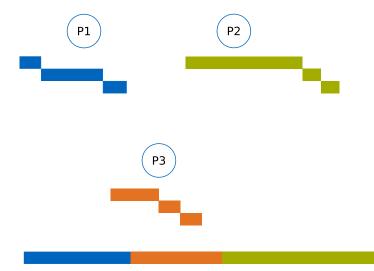
Given n parties  $P_1, \ldots, P_n$ . Each party  $P_i$  holds a secret value  $x_i$ . Secure Computation of  $y = f(x_1, \ldots, x_n)$  is performed if two conditions are satisfied:

- Correctness: the correct value of y is computed
- Privacy: y is the only new information that is released

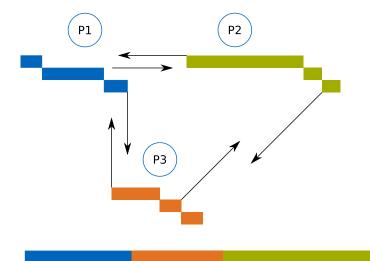












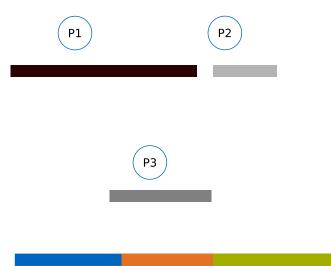




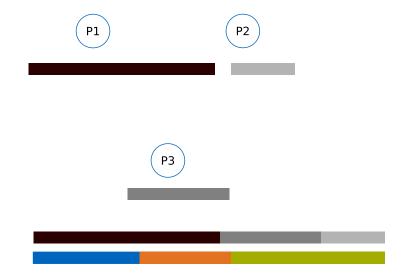


Marcel von Maltitz and Georg Carle — Leveraging Secure Multiparty Computation in the Internet of Things 10



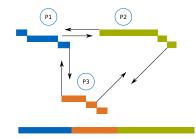




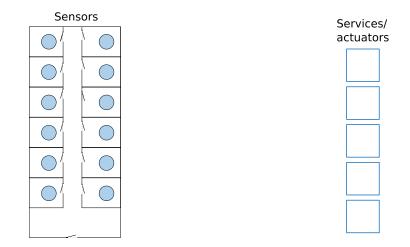


### Secure Multiparty Computation: Previous Applications

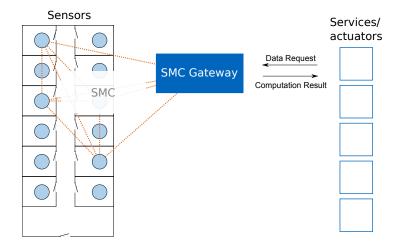
- (Double) auctions [2]
- EU emission trading scheme (CO<sub>2</sub> trading) [9]
- KPI ranking among companies [1]
- Network anomaly and outage detection [4, 7]
- Federated learning (distributed machine learning) [3]









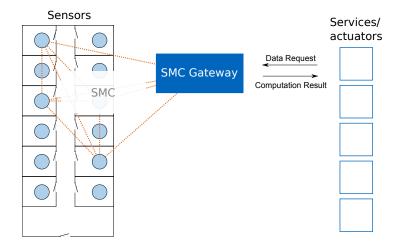






https://www.ge.com/digital/predix-platform-foundation-digital-industrial-applications







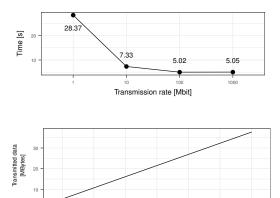
#### A Performance and Resource Consumption Assessment of Secure Multiparty Computation. M. von Maltitz and G. Carle. (2018, submitted)

#### Parameters

- #Nodes
- CPU #cores and frequency
- network latency
- transmission rate
- packet loss
- parallelization

#### Variables

- Execution time
- CPU consumption
- Memory allocation (stack, heap)
- Bandwidth usage



11

Number of Peers [#]

13

15

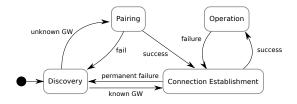


#### A Management Framework for Secure Multiparty Computation in Dynamic Environments.

M. von Maltitz, S. Smarzly, H. Kinkelin, and G. Carle (NOMS 2018, DOMINOS Workshop)

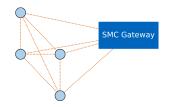
#### **Peer Orchestration**

- Discovery
- Pairing
- Recovery



#### **Session Management**

- Session Creation
- Peer allocation
- Monitoring
- Recovery



#### Access control and Accountability for Secure Multiparty Computation.

M. von Maltitz, D. Bitzer, and G. Carle. (2018, submitted)

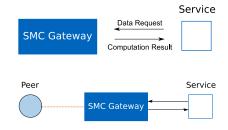
#### **Client Interaction**

- Request and query formats
- Request generation
- Access control and authorization
- Request  $\rightarrow$  session translation
- Result validation

#### Peer-side privacy protection

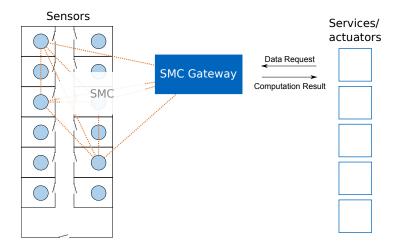
- Transparency of requests
- Intervenability upon computation
- Accountability of performed requests/ computations











### Bibliography

ТШ

- D. Bogdanov, R. Talviste, and J. Willemson. Deploying secure multi-party computation for financial data analysis. *Financial Cryptography*, pages 57 – 64, 2012.
- [2] P. Bogetoft, D. L. Christensen, I. Damgård, M. Geisler, T. Jakobsen, M. Krøigaard, J. D. Nielsen, J. B. Nielsen, K. Nielsen, J. Pagter, M. Schwartzbach, and T. Toft. Secure multiparty computation goes live.

In Lecture Notes in Computer Science, volume 5628 LNCS, pages 325-343, 2009.

- [3] K. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, and K. Seth. Practical Secure Aggregation for Privacy Preserving Machine Learning. In *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, volume 2017, pages 1175–1191, 2017.
- [4] M. Burkhart, M. Strasser, D. Many, and X. Dimitropoulos. SEPIA: Privacy-preserving Aggregation of Multi-domain Network Events and Statistics. *Proceedings of the 19th USENIX Conference on Security*, page 15, 2010.
- [5] H. Chan and A. Perrig. Security and privacy in sensor networks. *Computer*, 36(10):103–105, 2003.
- [6] R. Cramer, I. B. Damgard, and J. B. Nielsen. Secure Multiparty Computation and Secret Sharing. Cambridge University Press, New York, NY, USA, 2015.
- [7] M. Djatmiko, D. Schatzmann, X. Dimitropoulos, A. Friedman, and R. Boreli. Collaborative Network Outage Troubleshooting with Secure Multiparty Computation. *IEEE Communications Magazine*, (November):78–84, 2013.

### Bibliography



- [8] A. Ridi, C. Gisler, and J. Hennebert.
  A survey on intrusive load monitoring for appliance recognition.
  Proceedings International Conference on Pattern Recognition, pages 3702–3707, 2014.
- [9] M. Zanin, T. T. Delibasi, J. C. Triana, V. Mirchandani, E. Álvarez Pereira, A. Enrich, D. Perez, C. Paşaoğlu, M. Fidanoglu, E. Koyuncu, G. Guner, I. Ozkol, and G. Inalhan. Towards a secure trading of aviation CO2 allowance. *Journal of Air Transport Management*, 56:3–11, 2016.