DISTRIBUTED, INTELLIGENT EDGE-SENSING FOR A SMARTER GRID

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By

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Dedicated to my beloved family.

Your constant love and support has shaped me into the person I am today.
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TABLE OF CONTENTS

Acknowledgments ......................................................... iv

List of Tables ............................................................... xii

List of Figures .............................................................. xiv

List of Abbreviations ....................................................... xxiii

Key Definitions ............................................................. xxvii

Summary ................................................................. xxix

Chapter 1: Introduction ............................................... 1
  1.1 Motivation and Background ........................................ 1
  1.2 Research Scope and Objectives ...................................... 7
  1.3 Organization of Chapters ............................................. 8

Chapter 2: Literature Review and Prior Work ....................... 10
  2.1 Introduction ......................................................... 10
  2.2 Traditional Utility Sensor Networks ............................... 11
    2.2.1 Communication Systems for Distribution Grids ............. 11
    2.2.2 Edge-Computing Architectures for Smart Grids ............ 18
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.3</td>
<td>Smart Sensors for the Electric Grid</td>
<td>25</td>
</tr>
<tr>
<td>2.3.1</td>
<td>Current Sensing Solutions for Smart Grids</td>
<td>26</td>
</tr>
<tr>
<td>2.3.2</td>
<td>Rogowski Coil Current Sensors</td>
<td>36</td>
</tr>
<tr>
<td>2.3.3</td>
<td>Asset Monitoring Applications in Distribution Networks</td>
<td>44</td>
</tr>
<tr>
<td>2.4</td>
<td>Desired Attributes for a Low-Cost Scalable, Decentralized Smart Sensor Network for Distribution Grids</td>
<td>57</td>
</tr>
<tr>
<td>3.1</td>
<td>Introduction</td>
<td>60</td>
</tr>
<tr>
<td>3.2</td>
<td>GAMMA Platform Overview</td>
<td>62</td>
</tr>
<tr>
<td>3.3</td>
<td>Functional Elements of GAMMA Platform</td>
<td>66</td>
</tr>
<tr>
<td>3.3.1</td>
<td>End Node Design</td>
<td>66</td>
</tr>
<tr>
<td>3.3.2</td>
<td>Data Mules</td>
<td>69</td>
</tr>
<tr>
<td>3.3.3</td>
<td>Cloud Server</td>
<td>72</td>
</tr>
<tr>
<td>3.3.4</td>
<td>Network Setup</td>
<td>73</td>
</tr>
<tr>
<td>3.4</td>
<td>GAMMA Kernel</td>
<td>74</td>
</tr>
<tr>
<td>3.4.1</td>
<td>Attributes and Specifications</td>
<td>75</td>
</tr>
<tr>
<td>3.4.2</td>
<td>Memory Management</td>
<td>77</td>
</tr>
<tr>
<td>3.4.3</td>
<td>Energy Management</td>
<td>78</td>
</tr>
<tr>
<td>3.5</td>
<td>Communication Interface and Connectivity Models</td>
<td>79</td>
</tr>
<tr>
<td>3.5.1</td>
<td>Process of Pairing</td>
<td>81</td>
</tr>
<tr>
<td>3.5.2</td>
<td>Dependence on Radio Characteristics</td>
<td>83</td>
</tr>
<tr>
<td>3.5.3</td>
<td>Data Mule Mobility Models</td>
<td>84</td>
</tr>
</tbody>
</table>

Chapter 3: GAMMA Platform - Autonomous Distribution Grid Edge Monitoring and Control Platform
3.5.4 Simulation Results .................................................. 85

3.6 Experimental Feasibility of GAMMA Platform ...................... 88

3.6.1 Proof of Concept Application ................................... 88

3.6.2 Geo-location and Asset Tracking ................................. 90

3.6.3 Interfacing Specialized Peripherals and Global Operability .... 91

3.6.4 Field Test Results for Opportunistic Communication .......... 92

3.7 Concept of Distributed Intelligence at the Edge ................... 96

3.8 Comparison of GAMMA Platform with State-of-the-Art IoT Architectures ... 98

Chapter 4: Low-cost, “Clip-on” Current Sensor with Wide Dynamic Range . . 99

4.1 Introduction ................................................................. 99

4.2 Rogowski Coil Modeling and Operating Principles .................. 100

4.3 Lumped Parameter Model of PCB-based Rogowski Coil ............. 103

4.4 Variation of Mutual Inductance with Conductor Location .......... 109

4.5 Analog Design of the Signal Conditioning Stage .................... 112

4.5.1 Frequency Domain Behaviour of the Rogowski Coil Sensor ........ 112

4.5.2 Analog Design ......................................................... 113

4.5.3 Front End Amplifier .................................................... 114

4.5.4 Low Noise Integrator Stage ......................................... 115

4.5.5 Adaptive Programmable Gain Amplifier ......................... 116

4.5.6 Analog to Digital Conversion ....................................... 117

4.5.7 Overall sensor specifications ........................................ 118

4.6 Dynamic Range Correction Method .................................... 119
6.2.1 Instantaneous Auto-tuning, Fault Identification and Waveform Capture ............................................. 158
6.2.2 In-situ Waveform and Harmonic Analysis ................................................................. 159
6.2.3 Voltage and Power Quality Alerts ....................................................................................... 164

6.3 Analyzing Long Time-Horizon Data ......................................................................................... 166
6.3.1 Detection of EV Charging Activity ....................................................................................... 166
6.3.2 Detection of Reverse Power Flows Indicative of Roof Top PVs ...................................... 170

6.4 Impact of Distributed Edge-Intelligence .................................................................................... 172

Chapter 7: Conclusions, Contributions and Recommended Future Work ........................................ 173
7.1 Summary of Contributions ........................................................................................................ 175
7.2 Recommended Future Work .................................................................................................... 177
7.2.1 GAMMA Platform ............................................................................................................... 177
7.2.2 Smart Sensors for Network Management ........................................................................... 178

Appendix A: GAMMA Based Smart Meters and AMI Platform ...................................................... 181

Appendix B: EV Charging Detection Results on Prototype ............................................................. 186

Appendix C: Publications and Intellectual Property Generated through this Work ...................... 189
C.1 Journal Publications ................................................................................................................ 189
C.2 Conference Papers and Presentations ...................................................................................... 189
C.3 Patent Filings ............................................................................................................................ 190

References ........................................................................................................................................ 207
## LIST OF TABLES

2.1 Comparison of edge-computing nodes for smart grids proposed in literature .................. 23  
2.2 Smart current sensors proposed in literature .............................................. 34  
2.3 Comparison of Rogowski coils with other current sensing techniques ................. 36  
2.4 Rogowski coil based sensor designs proposed in literature ................................. 39  
2.5 Transformer sensor solutions found in literature ............................................. 52  

3.1 Comparison popular wireless protocols for smart grid sensor fusion ..................... 64  
3.2 GAMMA Kernel Specifications ....................................................................... 75  
3.3 Results from a stationary LOS field test ....................................................... 93  
3.4 Results from a field test of ‘Drive-by’ scenario .............................................. 94  
3.5 Results from a field test of ‘Bike-by’ scenario ................................................ 95  
3.6 Comparison of GAMMA with state-of-the-art ................................................ 98  

4.1 Comparison of expected and measured parameters of the printed coil at $f = 60$ Hz ........................................................................................................ 107  
4.2 Integrator op-amp characteristics .................................................................... 116  
4.3 Prototype sensor specifications ......................................................................... 118  
4.4 Results from interference test ........................................................................... 133  

5.1 Smart transformer sensor specifications ............................................................. 154
6.1 EV detection performance comparison from dataset consisting of 23 houses from [183] .............................. 170

A.1 Energy meter specifications .................................................... 182

A.2 Comparison of proposed solution with state-of-the-art .......................... 185
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Trends of exponential technologies— (a) US prices of solar (2018) [1], (b) Li-ion battery prices [2], (c) Cost and speed of computational resources [3].</td>
<td>2</td>
</tr>
<tr>
<td>1.2</td>
<td>Transition of the traditional grid to the smart grid of the future.</td>
<td>3</td>
</tr>
<tr>
<td>1.3</td>
<td>Two examples of issues caused by high penetration of ‘exponential technologies’— (a) Distribution voltage volatility [5], (b) Accelerated asset degradation [6].</td>
<td>4</td>
</tr>
<tr>
<td>1.4</td>
<td>Traditional approach for monitoring the distribution system involves instrumenting all assets with expensive sensors and high speed data links uploading raw data to the utility head end along with cloud-based analytics for deriving valuable insights.</td>
<td>5</td>
</tr>
<tr>
<td>1.5</td>
<td>The evolution of wireless telecommunication systems. <em>Courtesy of 3GPP-ITU.</em></td>
<td>6</td>
</tr>
<tr>
<td>2.1</td>
<td>Utility sub-systems along with the required communication attributes.</td>
<td>12</td>
</tr>
<tr>
<td>2.2</td>
<td>Compared to transmission systems, the distribution system has millions of distributed assets and communication systems for situational awareness.</td>
<td>13</td>
</tr>
<tr>
<td>2.3</td>
<td>Examples of communication architectures used for power grids (a) AMI and smart meter communication, (b) Sensors and SCADA systems [65].</td>
<td>15</td>
</tr>
<tr>
<td>2.4</td>
<td>Typical IoT-based implementations (a) [34], (b) Volttron platform [35].</td>
<td>17</td>
</tr>
<tr>
<td>2.5</td>
<td>Traditional models for edge computing follow a layered approach [41].</td>
<td>19</td>
</tr>
<tr>
<td>2.6</td>
<td>Edge computing applications for HEMs [44] and micro-grids [45].</td>
<td>20</td>
</tr>
<tr>
<td>2.7</td>
<td>Examples of load and waveform analytical methods (a) A NILM platform for building level demand response [49], (b) A waveform analytical tool developed for distribution grids [48].</td>
<td>21</td>
</tr>
</tbody>
</table>
2.8 Different current sensing approaches [64]— (a) Sense resistor (Ohm’s law), (b) Rogowski coil (Faraday’s law), (c) Current Transformer (Faraday’s law) (d) Open loop Hall effect sensor (Magnetic field sensing), (e) Closed loop magnetic field sensing, (f) Fiber-optics based on Faraday effect.

2.9 Solutions using magnetic flux sensors (a) Stick on sensor for overhead transmission lines [65], (b) Magnetic sensor array for home energy monitoring [67].

2.10 Examples of non-invasive ‘clip-on’ current sensors proposed in literature (a) Non-intrusive current sensor for two-wire power cords [70], (b) Zigbee-based electronic CT [75], (c) Direct-wire 3-D printed flexible CT [72].

2.11 Examples of Hall-effect based current sensors (a) Circular arrangement of Hall effect and GMR sensors [69], (b) Coreless current probe for conductors with reduced access [71], (c) Bluetooth-based smart connector [76].

2.12 Examples of commercial transmission line current sensors (a) Line Sentry by Grid Sentry LLC [78], (b) Gridsense LineIQ by FranklinGrid [79].

2.13 Fault current waveform and associated CT saturation [81].

2.14 Examples of waveform distortion caused due to current sensor limitations: Event ID #21852, #21831 and #21839 in [82]. Highly customized ‘smart sensors’ are needed for advanced distribution grid visibility.

2.15 PCB-based Rogowski coils proposed in literature— (a) A compact PCB Rogowski sensor [117], (b) A miniature square PCB Rogowski sensor for power electronic devices [118], (c) For measuring up to 300 kA current [119], (d) For sensing service transformer secondary currents [120], (e) Hybrid PCB self-integrating coils [113], (f) For detecting transmission line faults [80], (g) For detecting transmission line transients [121].

2.16 Instrumentation of sub-station LPTs. Courtesy of Principal Sales Inc.

2.17 A capacitor bank monitoring solution by a large US-based utility— (a) Schematic, (b) Field installation [138].

2.18 Distribution of transformer overloads over a year— (a) Based on the peak transformer utilization, (b) The number of total hours the transformers experienced overloads, (c) The maximum sustained period of overloading (on a log scale) [157].

2.19 Seasonal transformer loading profiles for Phoenix, AZ and Seattle, WA [158].
2.20 Abrupt step power changes in (noted by B and C) and rapid power fluctuations (seen in F, H) [160]. .......................................................... 49

2.21 Examples of commercially available solutions – (a) Distribution transformer oil monitoring system from Siemens [139], (b) Pole-top transformer monitoring solution OptaNODE Grid 20/20 from Itron [140]. .......................... 51

2.22 Experimental transformer condition monitoring implementations (a) Experimental setup from [153], (b) Setup from [154]. ................................. 55

3.1 Overview of GAMMA platform. The architecture offers an end-to-end solution with minimal customization. ......................................................... 63

3.2 Attacker model of the system: Bluetooth link (shown in blue) has link layer security, while cellular/Wi-Fi link (shown in green) has SSL (Secure Socket Layer) and TLS (Transport Layer Security). Weak attackers $W$ sniff packets, while strong attackers $S$ will try to infiltrate and impersonate. ............................... 67

3.3 Communication timing diagram. Time represented on vertical line. Blue links represent BLE and green links represent internet access to the GAMMA cloud. Since time between each step is non-deterministic, the entire network is delay tolerant. ......................................................... 68

3.4 Flowchart of the logic running on data mule app. ........................................ 70

3.5 GAMMA platform can enable an ecosystem of smart, autonomous devices that can perform control actions locally, while interacting with the cloud in a delay tolerant fashion. This is achieved by embedding the GAMMA Kernel in the end devices, making them compliant with GAMMA ecosystem. 74

3.6 GAMMA Kernel Block diagram and manufactured hardware. .................. 75

3.7 GAMMA Kernel memory interface. .......................................................... 77

3.8 GAMMA Kernel Power characterization during communication events. .... 78

3.9 Spatio-temporal representation of opportunistic connectivity. ................. 79

3.10 Time varying graphs when connectivity exists between end nodes and data mule only during specific time windows. ................................. 79
3.11 ‘Vertex centric’ evolution of the time varying graphs with presence and latency functions. It is assumed that the data mules always have a stable cloud connection (through cellular or Wi-Fi access). However, if internet access is unavailable, data can be locally cached and transmitted later.

3.12 Pairing process timeline. End nodes are BLE peripherals or ‘slaves’ while data mule applications on smart-phones act as BLE ‘masters’.

3.13 Evolution of $\rho$ for a given pair of data mule and end node. Connectivity indicates whether a data mule is in the vicinity of an end node.

3.14 Variation of BLE connection times— (a) For fixed $T_a$ and varying $T_s$, (b) For fixed $T_s$ and varying $T_a$.

3.15 Sample trajectories of data mules around the $x-y$ grid. The red dots show locations of end nodes ($N = 100$) while the colored traces are the trajectories of data mules ($M = 25$).

3.16 Variation of overall data throughput with number of data mules $M$ and over time.

3.17 Device package developed and deployed to test GAMMA platform. Plug-in power quality meter records and stores grid voltage events (sags, swells etc) and communicates to the cloud via the data mule app. The app has a user interface to pull data from the cloud and display to the user.

3.18 Voltage measurement and power quality event detection algorithm. Yellow trace is scaled voltage appearing on device ADC pin. Top traces (a) show AC voltage with a DC offset. Bottom traces (b) show AC voltage with an analog surge detecting circuit output.

3.19 Map shows GPS tags of datamules when the connections were established with GAMMA devices. On April 4th, device #5, connected at two different geographical locations. Analytics can detect & alert the fleet manager that the asset has been moved twice between April 4th & April 5th.

3.20 GAMMA based AMI unit, capable of smart metering, remote disconnect, VAR compensation. Prototype unit operated in Accra, Ghana (recorded location shown on top left). Two remote disconnect commands issued from Atlanta, USA to the device in Ghana.
3.21 Field tests performed in 3 locations (semi-urban, urban and rural) to find maximum distance at which a new BLE connection can be established (shown as D1, yellow trace being LOS) and maximum distance over which the connection can be sustained (shown as D2, red trace being LOS), between the GAMMA Kernel (denoted by ‘K’) & data mule app running on a generic mobile phone (denoted by ‘P’).

3.22 Drive-by scenario: Mobile phone (denoted by ‘P’) placed in generic car & driven around in urban (location 1) and semi-urban (location 2) locations. Map shows locations at which new BLE connection was established (shown in blue) and maximum LOS distance over which the connection could be sustained (red trace).

3.23 Drive-by scenario: Mobile phone (denoted by ‘P’) placed in generic car & driven around in semi-urban location. Tests at 30 km/hr (top) and 50 km/hr (bottom) show locations at which new BLE connection can be established (shown as D1, yellow trace) and maximum distance over which the connection can be sustained (shown as D2, red trace).

3.24 Proposed approach with GAMMA Platform and data mules can process most of the data on the sensor and upload alerts and summaries of recorded anomalies for the smart distribution grid.

4.1 Various components involved in a Rogowski coil based power line current sensor [90]. An integrator is required to get a signal proportional to the primary current $i_p(t)$ from the induced voltage $v_o(t)$.

4.2 Geometry of a PCB embedded Rogowski coil.

4.3 Lumped parameter model of a PCB embedded Rogowski coil.

4.4 Comparison of the four PCB-based Rogowski coils fabricated. Coils $C$ and $D$ can be clipped onto conductors.

4.5 Impedance trends of the unloaded coils tested on Agilent™ E4990A Impedance Analyzer. No resonance observed till $f = 10$ MHz, indicating $f_r > 10$ MHz.

4.6 Comparison of the coil outputs when excited by primary current $i_p = 1.2$ A$_{rms}$ at 60 kHz.

4.7 (Green trace) Step response of coil D for a (pink trace) 100 kHz, 333 mA$_{pk-pk}$ square wave primary current, $i_p$. Zoomed in version shows fast settling time ($< 200$ ns).
4.8 Variation of the mutual inductance $M$ with conductor position inside the Rogowski coils (coils C and D). Up to $\pm 3\%$ variation is observed.

4.9 Frequency domain design of Rogowski coil sensor: Red trace shows the frequency response of the Rogowski coil, green trace shows analog integrator response and blue trace shows the combined response of the coil and integrator.

4.10 Waveform clipping due to signal conditioning circuit’s finite rail-to-rail swing.

4.11 Block-diagram of the analog signal conditioning stage.

4.12 Illustration of the front end amplifier.

4.13 Illustration of ‘Dynamic Range Correction’. Output of sensor with and without DRC. Without DRC, sensor saturates at rail voltages, offering limited dynamic range during fault currents.

4.14 Typical sensors will saturate around $3 - 5$ V, which is the full scale of the ADC. With DRC, the gain is adjusted to map the current waveform to the full scale range of the ADC.

4.15 Based on the calculated value of $dv/dt$ as shown above, gain $G[n + 1]$ is adjusted so that the raw sample value $v[n]$ is maintained between 0 and 3000 mV to avoid distortion.

4.16 (a) Test schematic, (b) Setup and (c) Manufactured prototype with different sections labelled.

4.17 Transient response of the integrator (a) SPICE simulations at 60 Hz (b) Hardware tests at 60 Hz (c) SPICE simulations at 600 Hz (d) Hardware tests at 600 Hz. As seen in the hardware tests, the integrator (red trace) settles in 2 – 5 cycles when a simulated fault current $di/dt$ input (green trace) is applied.

4.18 (a) Fast settling design for the signal conditioning stage, (b) Signal settling time for a gain switch, (c) Overall signal transition.

4.19 Sensor output at various frequencies: 60 Hz, 600 Hz, 6 kHz, 60 kHz sinusoidal excitation and at 15 kHz square and triangular wave excitation.

4.20 Frequency response of the sensor from $i_p(t)$ to sensor output $v(t)$. Note that the magnitude response can be adjusted by DRC.
4.21 Setup to circulate high current in a loop. A comparison of the form factors of Pearson current probe [170] and proposed sensor is shown.

4.22 Sensor output for various input current levels at 60 Hz.

4.23 Test waveforms for the DRC algorithm. \( di/dt \) signal corresponding to the current shown is applied to the integrator stage, and varied with time. As the current levels increase, the MCU adapts the gain to center the sensor output near the ADC full scale and does so without any distortion of the raw sampled signal.

4.24 Fault current capture from 410 A\(_{rms}\) steady state to \( \sim 21 \) kA\(_{rms}\). (a) Oscilloscope waveforms (b) ADC sampled data on the sensor (c) Reconstructed waveform.

4.25 Fault recovery from 50 kA\(_{rms}\) to 330 A\(_{rms}\). (a) Oscilloscope waveforms (b) ADC sampled data on the sensor (c) Reconstructed waveform.

4.26 Setup to generate high current impulse using a co-axial winding transformer (CWT). The thyristor was triggered to discharge the capacitor into the primary (50 turns) of the CWT with the single secondary turn shorted, generating an impulse of 19 kA\(_{pk}\).

4.27 Output of the sensor during pulse test. Sensor does not saturate at high impulse current.

4.28 Noise spectra at various stages of the sensor system. The \( di/dt \) signal itself, at the output of the Rogowski coil has a very poor SNR (\( \sim 20 \) dB). This makes it infeasible to use the incoming \( di/dt \) signal itself for dynamic range correction.

4.29 Setup to perform interference test. \( i_1 \) is the current being measured and \( i_2 \) is the external noise source, placed at a distance of 5 cm from the Rogowski coil.

4.30 3-D printed package and PCB for the current sensor (a) Final packaging, (b) Assembled PCBs.

4.31 Adaptable hardware that can be utilized with different types of applications.

5.1 Hardware overview of the proposed smart transformer monitor.

5.2 Current sensor interface with the \( \Sigma - \Delta \) ADC in the energy metering AFE.
5.3 Manufactured smart transformer monitor. ........................................... 142

5.4 Software overview of smart transformer monitor. ................................. 144

5.5 Experimental setup for validating the sensor performance (a) Circuit dia-
gram, (b) DUT transformer with sensor mounted, (c) Close-up of the sensor. 146

5.6 Linearity, variation of gains through DRC and errors in current measure-
ment from 50 mA to 1800 A. ............................................................... 147

5.7 Trend of voltage measurements (a) Linearity curve (b) Trend of errors. . . 148

5.8 Current (pink trace) and voltage (green trace) waveforms and correspond-
ing measurement data recorded by the sensor. ..................................... 149

5.9 Illustration of the sensor commissioning process. ................................. 151

5.10 Screenshots showing transformer sensor data displayed in the GAMMA
mobile application— (a) Case and ambient temperatures, (b) Active and
apparent energy, (c) Voltage. ............................................................... 152

5.11 Field demonstration with utility partner— (a) Bucket truck roll, (b) Instal-
lation of unit #1 on an energized transformer, (c) Unit #1 operating in the
field, (d) Installation of unit #2 on a de-energized transformer, (e) Unit #2
operating in the field, (f) Utility crew and CDE team validating the perfor-
mance of unit #2 in the field. .............................................................. 153

6.1 Categorization of edge-analytics supported by the sensor. .................... 157

6.2 Circuit to create a dead-short fault on a distribution transformer. ............ 159

6.3 Waveform of a 2650 A_{pk} fault observed on a pole-top distribution trans-
former captured through the transformer sensor prototype. Inset— Digi-
tized waveform. .............................................................................. 159

6.4 Comparison of outputs recorded from Pearson current probe [170] and
transformer sensor prototype. The black trace is the current sensor’s volt-
age output waveform captured on an O’scope, while the red trace is the
digitized waveform captured on the sensor. ........................................ 160

6.5 Comparison of (a) Peak current captured on transformer primary (actual
corresponding current is 30\times lower) and (b) Digitized current captured by
the sensor. ....................................................................................... 161
6.6 Illustration of waveshape distortion ........................................ 162

6.7 FFT computation results for current waveforms that are (a) Sinusoidal (b) Triangular and corresponding captured waveform snippet. Comparison of spectra with MATLAB-based FFT computation of an ideal waveform. . . . 163

6.8 Comparison of sensor computed FFT spectra with MATLAB computation for waveforms that are – (a) Sinusoidal, (b) Square, (c) Triangular (d) Sawtooth. .............................................................. 164

6.9 Sag events captured by the sensor (a) Voltage sag 6 cycle, down to 120 V_{rms}, (b) Voltage sag 6 cycle, down to 180 V_{rms}. ......................... 165

6.10 Swell events captured by the sensor 6 cycle, up to 270 V_{rms}. ............ 165

6.11 Aggregated 24 hr current profile for houses #1 – 3 and 7 along with ground truth EV profile, sensor’s estimate compared to [50]. ................. 168

6.12 Aggregated 24 hr current profile for house #2 along with ground truth EV profile, sensor’s estimate compared to [50]. It can be seen that a false negative has been recorded using the algorithm in [50]. ................... 169

6.13 Phase reversal indicative of reverse power flow. ............................. 171

A.1 Design of a smart meter with pay-as-you-go capability and VAR compensator.182

A.2 (a) Setup to experimentally verify pay-as-you-go and VAR compensation functionality, (b) Waveforms for smart shut off, (c) Offline communication capability. ................................................................. 183

B.1 Sensor-based edge computing outcome for homes #1 – #12 ............ 187

B.2 Sensor-based edge computing outcome for homes #13 – #23 ............ 188
List of Abbreviations

2G/3G/4G/5G – Cellular communication generations

ADC – Analog to digital converter

AES – Advanced encryption standard

AFE – Analog front end

AP – Access point (typically an internet access point)

API – Application programming interface

AMI – Advanced metering infrastructure

AMR – Automated meter reading

ARM – Advanced RISC Machines

BLE – Bluetooth Low Energy (i.e. Bluetooth 4.2)

BOM – Bill of materials

CDE – Center for Distributed Energy

CPU – Central processing unit

COTS – Commercial off-the shelf

CT – Current transformer

DAQ – Data acquisition card

DER – Distributed energy resource

DGA – Dissolved gas analysis

DRC – Dynamic range correction

DSP – Digital signal processor

DTN – Delay tolerant network

DUT – Device under test

E2EE – End-to-end encrypted

EIRP – Effective isotropic radiated power

EMI – Electromagnetic interference
EMS – Energy management system

EV – Electric vehicle

FFT – Fast Fourier transform

GAMMA – Global Asset Monitoring, Management & Analytics

GMR – Giant magneto-resistance

GPIO – General purpose input output (pins available on MCUs)

GPS – Global positioning system

GSM – Global system for mobile communication

HAN – Home area network

HEMs – Home energy management system

HTTP – Hyper-text transfer protocol

I2C – Inter integrated circuit

IC – Integrated circuit

I/O – Input output

IoT – Internet of things

IR – Infra-red

IT – Information technology

LAN – Local area network

Li-ion – Lithium ion (battery chemistry)

LoRa/LoRaWAN – Low power, long range wide area networking

LOS – Line of sight

LP-WAN – Low-power wide area network

LPF – Low pass filter

LPT – Large power transformer

M2M – Machine to machine

MAC – Media access control

MANET – Mobile ad-hoc network
MAS – Multiple address radio
MCU – Micro-controller unit
MDMS – Meter data management system
MEMS – Micro electro-mechanical system
MSE – Mean squared error
MV – Medium voltage (1 – 69 kV)
NB-IoT – Narrow band Internet of things protocol (a low-power wide area network)
NIC – Network interface card
NILM – Non-intrusive load monitoring
NV – Non-volatile
OLTC – On-load tap changer
PAYGO – Pay-as-you-go
PC – Personal computer
PCB – Printed circuit board
PD – Partial discharge
PGA – Programmable gain amplifier
PLC – Power line communication
PMU – Phasor measurement unit
PQ – Power quality
PV – Photo-voltaic
RAM – Random access memory
RF – Radio frequency
RFE – Radio front end
RFID – Radio frequency identification
RMS – Root mean squared
ROI – Return on investment
RTC – Real-time clock
RTOS – Real-time operating system
RTU – Remote terminal unit
SAIDI – System average interruption duration index
SAIFI – System average interruption frequency index
SAR – Successive approximation register
SCADA – Supervisory control and data acquisition
SCR – Silicon controlled rectifier (thyristor)
SOC – System on chip
SNR – Signal to noise ratio
SPI – Serial peripheral interface
TCP/IP – Transmission control protocol and internet protocol
THD – Total harmonic distortion
UART – Universal asynchronous receiver-transmitter
UI/UX – User interface/User experience
USB – Universal serial bus
UTC – Universal time coordinated i.e. Greenwich Mean Time (EDT + 5hrs)
VVC – Volt-VAR controller
WDT – Watch-dog timer
WLAN – Wireless local area network
WiMAX – Worldwide Interoperability for Microwave Access (IEEE 802.16)
Wi-Fi – Wireless Fidelity (IEEE 802.11x)
Key Definitions

AMI — Smart meters and associated components within Advanced Metering Infrastructure.

App — Mobile phone application.

Autonomous operation — The ability for nodes to operate based on local conditions without relying on cloud inputs.

Back-haul network — The network infrastructure that exists behind an Internet AP, connecting it to the cloud from the field. E.g. A router in the field may have internet access through fiber-optic, LAN or cellular networks.

Cloud — A set of servers that are accessed over the Internet, and the software and databases that run on those servers. The infrastructure could use dedicated, server-hardware based resources, or standard serverless, service-based platforms.

Data mule — A device (e.g. a mobile phone, drone, utility truck etc.) that can bridge the last mile connectivity gap and relay data between two end points, typically a device in the field and the cloud entity.

Decentralized — Individual local action without full global information, typically without relying on a central coordinating entity like a cloud server.

Delay Tolerant Networks — Networks that can lack continuous connectivity and can thus operate with high latencies, often hours to days.

Distributed — Geographically dispersed, located in different locations.

Dynamic Range of a sensor — The ratio of lowest measurement possible, to the highest measurement possible with a sensor. E.g. if a sensor can measure from 10 A to 1,000 A, then the dynamic range is expressed as 1 : 100.

Edge-computing — Computation performed at or near the source of the data, instead of relying on the cloud.

Grid-edge — At the periphery of the power grid infrastructure, typically at the distribution grid’s low-voltage side at the point of connection for customers.
Non-intrusive load monitoring — Load dis-aggregation or methods to identify constituent energy consuming loads based on aggregated power/energy/current measurements.

Real-time — When a response (or in case of a network, the latency) is within a few milliseconds.

Scalable — A way to replicate and reproduce an entity in large numbers in a given system, with the assumption that the per unit cost of the entity would go down as the system is deployed in large numbers.

Utility companies — Electric utilities, the corporations that are responsible for generation and distribution of electrical energy.
Summary

The electric grid is undergoing a major transformation, from a centralized, unidirec- 
tional and deterministic system to a decentralized, bidirectional and stochastic system. This 
transition is mainly fuelled by exponential technologies including DERs (like PV, wind), 
energy storage and semiconductor based technologies like power electronics and micro-
controllers. Many of these changes are being implemented on the distribution side of the 
grid through increased penetration of EVs, rooftop PVs, smart inverters etc. To maintain 
visibility and control over the complete network, it is imperative for grid operators to rely 
on sensors and instrumentation techniques. The vast advances in digital and communi-
cation technologies have made it possible to connect each and every device to the cloud, 
transforming them into ‘smart sensors’. This ‘IoT revolution’ has helped in the rapid adop-
tion of smart grid technologies.

The progress in IoT technology has made it possible for researchers to develop, and 
for electric utilities, to deploy numerous sensor networks in the power grid. This broader 
adoption has been possible due to many popular short range radio protocols used for com-
munication, with several standards emerging. As a result, a few state-of-the-art architec-
tures for implementing sensor networks in the power grid have emerged. They rely on the 
presence of a dedicated wireless internet access point in the field, and point to point radio 
links between the sensors. These models have traditionally used expensive sensors report-
ing raw data to the cloud for computation and processing, and receiving specific commands 
for executing control sequences, resulting in a system that relies on high-bandwidth, low-
latency communication networks and a centralized repository of time-series data on the 
cloud.

This approach scales well when the assets being monitored are few in number and are 
highly critical for the overall operational stability of the power grid and when the cloud is responsible for ‘closing the operational loop’. For instance, in the bulk transmission
system or sub-stations, it is possible to instrument few critical assets for the purposes of health monitoring and reporting periodic status updates.

By contrast, the distribution network is very different from the transmission and sub-transmission grids. It spans vast geographical areas and has an order of magnitude larger number of assets. The distribution grid also has a more diverse range of assets, with each asset value being fractional compared to those of transmission systems. As the number of distributed sensors and actuators connected to the grid increase almost exponentially, a centralized connectivity model fails to be economically viable. Moreover, the cost of each sensor (both capital and operational) must be proportional to value of the asset being monitored for the approach to provide any justifiable return on investment. The sensors, fundamentally measuring voltage and current, also suffer from a high level of customization and complex installation and configuration procedures in the field. A radically different approach is needed to obtain advanced visibility into the distribution grid, at ultra-low cost without compromising performance.

In this work, a decentralized architecture is proposed, where sensing, local computation and control capability are embedded in the edge devices. These devices report only actionable information to the cloud, resulting in a lean ‘delay-tolerant’ system that can function autonomously. The proposed system leverages smart phones and other low-cost relay devices to opportunistically network and securely bridge the last mile gap. This system has been designed and implemented as an overall platform—called Global Asset Monitoring, Management and Analytics (GAMMA) Platform intended to provide the backbone for a global array of sensors and actuators.

For an electrical network, voltage, current and frequency represent key parameters that need to be monitored to assess the health of the system or for millions of assets in it. In particular, current sensors are fundamental to the operational visibility into distribution networks revealing information about the stress and loading levels experienced by the ageing distribution infrastructure. The occasional faults, power disturbances, abnormal harmonics
all contribute to the degradation of assets in the distribution system. A new class of sensing solutions have been developed that can help with this situational awareness in smart distribution grids.

The proposed system leverages smart, low-cost ‘clip-on’ current sensors based on PCB-embedded Rogowski coils. They are developed to be retrofitted onto conductors in the field. Additionally, a novel, adaptive signal conditioning stage and a new method to improve the dynamic range of the current sensor has been developed, resulting in performance that is orders of magnitude better than state of the art sensors. The sensor is designed to be low-cost and yet, covers a wide range of operating ranges and modes, including edge-computation, intelligence and communications.

Finally the research proposes a method to instrument and monitor the most common electric utility asset— the pole-top distribution transformer. The sensor, essentially a smart-metering device, is capable of recognizing operational anomalies like faults, power quality disturbances, abnormal pole tilts and temperatures and can be used by utility operators to gain advanced situational awareness in distribution networks. The novel sensor design and the decentralized architecture allows utility operators to intelligently monitor transformers and other utility assets at an ultra-low cost. The proposed research can result in a new class of devices that can help in monitoring distributed utility assets in an economical way.

Overall, this project identifies the issues related to situational awareness and control of massively distributed assets, particularly on the distribution grid. It then develops and demonstrates a solution that is both technically viable and seems to be economically attractive.
CHAPTER 1
INTRODUCTION

1.1 Motivation and Background

The electric grid has been operational for the past 100+ years. Over the past several decades, it has evolved through various generations of technologies—from slow electro-mechanical controls to fast acting micro-processor and electronics-based systems. The grid originated as a centralized, top-down system of thousands of interconnected generators, transformers, transmission, distribution lines and loads; that worked through planning and design. Switches and relays were used to to connect or disconnect entire circuits for operational and protection purposes. This ‘top-down’ and planning-based architecture along with the basic operating principles have remained largely unchanged over the last 100+ years.

However, in the past two decades, the advent of sophisticated electronic components, such as microprocessors, PMUs, sensors, and communications devices; have allowed the grid operators to have better visibility and situational awareness across the network. Operators are now able to use advanced tools such as state estimation, optimal power flow control and security constrained economic dispatch, to better manage and optimize the operation, reliability and economics of the power system. However, their ability to effect change has, until recently, been limited to relatively coarse and slow electro-mechanical control.

We can see that this paradigm is drastically changing— the rapid growth of exponential technologies, such as solar PV, wind, batteries, semiconductors and microcontrollers, all following some version of a ‘Moore’s Law’\(^1\) with continually declining prices and improving performance; is forcing a re-evaluation of what the future grid could look like.

\(^1\)Moore’s Law refers to Gordon Moore’s perception that the number of transistors on a microchip doubles every two years, though the cost of computers is halved.
Figure 1.1: Trends of exponential technologies — (a) US prices of solar (2018) [1], (b) Li-ion battery prices [2], (c) Cost and speed of computational resources [3].

Fig 1.1 shows the prolific, almost exponential decline in prices for PV, battery storage and computing resources, including internet connectivity over the past few years.

This paradigm shift is driving a fundamental change in the operating regime [4]. From a centralized, ‘top-down’ architecture with large generators being dispatched to follow load, the grid is evolving into a highly decentralized network, as shown in Fig. 1.2. In this scenario, variable DERs (e.g. wind and solar) are being balanced in real-time through the autonomous action of millions of ‘prosumers’, using loads or local generation to achieve this balance. The network was not initially designed for these changes and thus it becomes imperative for grid operators to have a high level of visibility into the network. This helps in maintaining and improving reliability standards as well as overall control over the system. The ability to sense across millions of geographically dispersed assets and source/load centers, to act locally, and to coordinate and optimize at a global level, all at ultra-low-cost, poses a tremendous challenge, one for which there seems to be no economical solution that

\[2\]Decentralized refers to individual local action without full global information
Sensors that record current, voltage and power are indispensable for utility operations and have been widely used for situational awareness, state estimation, metering, assessing the health of power equipment and optimizing operational states. The sensors may be integrated with data acquisition systems that also process the voltage and current data over time, storing the data and making it available as specified. Typically, utilities periodically request time-stamped data from each sensor for their operational routine. Each sensor, equipped with some backhaul communication link reports data to the cloud server, where computational algorithms help utilities in determining the system status.

For several decades, the electric grid has been successfully designed and operated using this centralized, planning-based approach. Utility operators have instrumented and controlled a few critical assets, typically in the transmission and sub-transmission systems. These assets are expensive and critical for overall utility operations, thus justifying the need as well as methods employed for gaining visibility.

However, as the adoption of DERs gains momentum, particularly in the distribution
networks, the decades-old planning-based, top-down approaches get challenged and new decentralized, variable operational strategies emerge. Sometimes, these approaches can cause unforeseen issues in the distribution network. For instance as shown in Fig. 1.3, increased voltage volatility is caused due to high penetration of PV resources [5] and accelerated asset degradation [6] due to heavy power-electronic loads like EV charging stations. This paradigm shift has brought about a strong need for asset monitoring and management for advanced and pro-active situational awareness.

![Figure 1.3: Two examples of issues caused by high penetration of ‘exponential technologies’ — (a) Distribution voltage volatility [5], (b) Accelerated asset degradation [6].](image)

To this end, utilities have tried to implement advanced distribution management systems with sophisticated sensors and real-time communication networks as shown in Fig. 1.4. However, this approach fails to deliver acceptable returns on investment. This is mainly because the number of end points to be monitored ranges in millions, while the cost of each asset and the economic value delivered to the end-customer are orders of magnitude lower compared to the bulk transmission systems. Besides, the assets in distribution systems can be geographically dispersed. They are generally located in areas where establishing the ‘last mile connectivity’ can be challenging and expensive. Moreover, utilities have to keep up with changing wireless networking standards, which tend to migrate faster
than the lifecycle of typical utility assets (10 – 20 years). The evolution of telecommunication standards over the past 40 years has been depicted in Fig. 1.5.

The above discussion alludes to the fact that as the grid evolves due to the growing adoption of these exponential and rapidly proliferating technologies, a fundamental change is necessary for obtaining higher levels of visibility into the grid—particularly the distribution network. A highly decentralized strategy needs to be adopted, one that can scale to millions of devices across geographic borders. The ability to sense across millions of distributed assets, to act locally, and to coordinate and optimize at a global level, can be significantly challenging. The solutions needed here have to operate in rural areas with poor/no connectivity, and sometimes have to capture fast, sub-cycle events for diagnostic purposes. For the strategy to be economically viable, individual solutions must be ultra-low

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3Distributed here refers to geographically dispersed
cost and customization of the solution is to be minimized.
1.2 Research Scope and Objectives

The objective of this research is to develop low-cost, autonomously operating grid edge sensors with integrated analytics for the distribution grid. The sensors operate using a novel communication and data processing architecture that is highly suitable for monitoring assets located in arbitrary, remote locations.

The scope of this work can be summarized into three categories as follows—

1. Developing a novel communication and edge-computing architecture: For distribution networks, establishing and maintaining point to point last mile connectivity can be challenging and very expensive. Moreover as communication standards evolve utilities are faced with expensive technology migration exercises. As smart grid solutions are deployed across the world, global compatibility is a concern. As decentralized operational architectures emerge, processing information at the ‘edge of the network’ has several benefits which can be result in lean communication systems.

2. Designing novel current sensors for the distribution grid: For advanced visibility and situational awareness, current sensors play a vital role. However, for low-cost sensing, a technique compatible with mass-manufacturing and quick field installation needs to be developed. Typically, each current sensor is ‘tuned’ for measuring a particular current level. However, it can be invaluable to capture anomalies like the rare system faults when the current can rise to $>10 \times$ the nominal value. Another pain point is the expensive customization effort for matching different sensor to the current levels being monitored. As no solution presently exists that have these features, significant research efforts are needed. Thus, this thesis focuses on developing an advanced current sensor solution that can offer a significant performance upgrade for existing current sensors.

3. Designing novel asset monitoring applications based on above technologies: A new type of sensor for asset monitoring for pole-top distribution transformers has been
discussed. This showcases the practical viability of the above mentioned communication platform and current sensor.

1.3 Organization of Chapters

Chapter 1—An overview of the research scope, objectives and expected outcomes has been presented in this chapter. The chapter also discusses the need for developing novel, intelligent sensing and networking techniques for the distribution grid.

Chapter 2—This chapter presents a critical review of existing literature on three fronts—

1. Sensor networks for the distribution grid monitoring with a focus on edge-computing techniques.

2. Review of smart sensors, in particular advanced current sensors based on Rogowski coils.

3. Asset monitoring solutions for monitoring distribution transformers.

In each of the above section, key features and fundamental drawbacks have been discussed. The discussion lends itself to desirable attributes for a viable low-cost sensor for the distribution system, thus concluding the chapter.

Chapter 3—A unique sensor network architecture, called GAMMA (Global Asset Monitoring, Management and Analytics) Platform, based on autonomous, intelligent end nodes and Bluetooth and smart phone-based opportunistic networking has been proposed. A detailed discussion on the design principles, the features of different components and implementation has been presented. Few simulations and experiments have been conducted to show the practical viability of the platform.

A unique architecture for distributed ‘edge-intelligence’ that transforms low-cost sensors into smart, edge computing nodes has been presented.
Chapter 4—This chapter details the design of a low-cost, “clip-on” current sensor based on PCB-embedded Rogowski coils. A first principle’s design approach and analysis has been presented, along with the experimental validation. Next, a fundamental drawback in the dynamic range of traditional Rogowski coil sensors has been presented. A new adaptive signal conditioning stage along with an approach to improve the dynamic range of the Rogowski coil sensor has been presented. Experimental validation of the proposed sensor shows practical viability. Finally, the design of a universal AC current sensor has been developed, intended to be used in stand-alone current monitoring applications or to be embedded in more advanced sensors for situational awareness in the grid.

Chapter 5—In this chapter, a smart sensor has been developed for monitoring different parameters of a distribution transformer. The sensor looks at the transformer holistically and extracts parameters of interest, indicative of the performance and degradation. These features are reported to the utility operators on a priority basis and provide insights into the asset operation and health. The sensor includes the PCB-Rogowski coil sensor and uses GAMMA platform for communication and distributed edge-intelligence. Details from experimental and field validation have been presented in this chapter. Compared to the traditional sensor networks using a centralized server-based architecture, the proposed system can operate in arbitrary locations and is economically viable.

Chapter 6—Experimental validation of a few analytical features that have been made possible through embedded edge-intelligence have been presented. The capability of the sensor to process information locally, on varying time-scales ranging from a few line cycles to few days has been showcased.

Chapter 7—This chapter, summarizes the key findings from this research. The major contributions from this work have been listed and a few possible future research directions has been discussed. This chapter concludes the thesis.
2.1 Introduction

As the electric grid transitions into a highly distributed and intelligent grid, with a high penetration of variable energy resources (like PV and wind), the traditional ‘top-down’ operational paradigm is significantly challenged. The unprecedented stress experienced by utility assets across the electric grid is very concerning. As a result, electric utilities are increasingly focusing on the monitoring and management of asset health and performance in their networks.

However, a unique predicament exists in the distribution grid, compared to the generation, transmission and sub-transmission networks. Among all the sub-systems, the distribution grid is facing the most transformations at a rapid pace. The type of assets found in the distribution network also differ significantly from those found in other sub-systems. The distribution grid assets are lower in overall costs and value, while also being significantly higher in number and located in geographically distributed locations.

As technologies that enable sensing, computation and communication become inexpensive and ubiquitous, low-cost asset monitoring becomes feasible. Most implementations adopted by electric utilities, or those found in literature rely on techniques broadly popularized by ‘internet of things’ technologies. Some of these methods can prove to be difficult to deploy, manage and maintain in a way that is economically feasible. This chapter reviews some of the approaches found in literature and analyzes their shortcomings.
2.2 Traditional Utility Sensor Networks

Electric utilities have to coordinate dispatch, manage and maintain their large critical assets like generators, large power transformers and key interconnections. For decades, utilities have been using various communication platforms [7] - [15] and have gone through numerous ‘generations’ of communication technologies. With critical elements at the bulk generation and transmission level and with coordination being necessary for system integrity and stability, low-latency communication is important for this asset base. Utilities have used private cellular networks, fiber and microwave communications [7] - [12] to manage their Energy Management Systems (EMS). However, this is restricted to a small number of assets, where the cost and complexity of installing, operating and maintaining the communications and security layer can be justified for the critical and expensive infrastructure. This provides connectivity to a few thousand important assets and ensures security, absolute control of their networks and priority in information flow.

2.2.1 Communication Systems for Distribution Grids

As we move towards a distributed and decentralized world, and begin to look at the electric distribution system, we see millions of devices, including transformers, capacitors, switches, PV inverters, loads, prosumers— all of which need to provide data for situational awareness, and to coordinate their own actions to support the grid and improve system robustness and stability. Solutions that have traditionally worked for generation and transmission systems would not necessarily work with distribution systems [13] - [14], as the asset class is significantly different. Compared to the bulk transmission system, the assets in the distribution network are more diverse, lower in value and much larger in numbers. Unlike for industrial plants, utility assets can be geographically dispersed, often times located in remote areas with poor connectivity. This makes the challenge of connecting millions of devices to their own cloud very complex and expensive.
Fig. 2.1 shows typical applications in each of the power grid sub-systems, with the requirements for the communication channels at different levels.

Fig. 2.2 shows the electric distribution system with a variety of assets that need to communicate with the cloud for situational awareness. These include advanced metering infrastructure (AMI), distribution system assets like transformers, capacitor banks, sectionalizers etc. Other systems like EV charging stations, connected power electronic devices like smart inverters, solid state transformers, distributed energy resource management systems are also capable of sensing, actuation, communication and cloud based functions. The communication technologies traditionally used [7] - [18] include (but not limited to) power line communications (PLC), multiple access radio (MAS), 900 MHz networks, meshed radio networks, private cellular backhauls, WiMAX, etc.

Many electric utility assets like line-breakers, reclosers, sectionalizers, in the subtransmission or distribution network, have been operated autonomously. Since these are controllable assets, electric utilities have relied on cellular communication or other proprietary radio systems to connect them to their control infrastructure for advanced situational
Figure 2.2: Compared to transmission systems, the distribution system has millions of distributed assets and communication systems for situational awareness.

In many ways, the task of managing millions of smart assets in a decentralized smart grid looks like a variation on an Internet of Things (IoT) application [18] - [22], with some similarities and several key differences. Overall, ultra-low-cost is required because of the large number of devices, the low cost of individual assets and the low cost of energy delivered. Autonomous control maybe needed at the edge, along with broad central coordina-
tion. Energy management can have a big impact on the cost, size and viability of these edge devices. Intelligence and machine learning are key to getting local and system level optimization. Connectivity of these edge devices to the cloud is sometimes done using cellular modems, or more typically using a remote terminal unit (RTU) [10] connected to the cloud via a private network. However, cybersecurity is a major issue for utilities and needs to be addressed. Rapid technology migration in the telecom sector also creates a major challenge [14], [16] for utilities that are accustomed to designing their systems for 25+ years of life. Further, the integration of these smart and connected devices with their physical electrical network and with their transactional processes (e.g., for smart meters), and the operational task of managing a large fleet of such devices requires tremendous customization effort, with resulting high cost.

Utilities have adopted several architectures for smart grid communications [7] - [12], especially for the electric distribution system. The preferred ‘hierarchical’ architectures like those adopted for smart meter/AMI communications and SCADA systems are shown in Fig. 2.3.

Several IoT implementations have also recently appeared in literature [18]. These include short range radios like Wi-Fi [23], Zigbee [24], Z-wave [25], Bluetooth [26] - [28]. With advances in the field of IoT, several machine-to-machine (M2M) connectivity protocols have been deployed [29]. Similarly, long range radios like Low Power Long Range Radio (LoRaWAN) [30] or IPv6 over Low Power Personal Area Networks (6LoWPAN) [31] can also achieve M2M connectivity and a data aggregator is typically used to connect to multiple device in the field and relay data back to the cloud. These schemes rely on internet access points (AP)\(^1\), usually in the form of wired (PLC, LAN or fiber-optic) or wireless (cellular, Wi-Fi/WiMAX) transponders.

The traditional solution for ‘smart devices’, relies on high bandwidth [32], low latency communications [33] to push sensed parameters to the cloud, use cloud computing to

\(^1\)Sometimes, in IoT terminology, this is referred to as a ‘gateway’ device or ‘aggregator’
realize certain control action and then push commands back to the devices to achieve the desired response. Bandwidth and latency requirements are dictated by the type of application [7] - [18]. Typically, utility operators prefer high-bandwidth, low-latency communications for fast, ‘real-time’ response and absolute control. However, this is achieved at a significantly high cost and complexity of operation. Often times, these are totally avoidable in asset monitoring applications, where the degradation cycles and events occur at a much slower pace.
Significant prior work related to smart grids and energy systems exists in the broader IoT space (examples shown in Fig. 2.4). Several communication architectures have been proposed and popularly adopted for smart grids, especially for the electric distribution system [8], [10], [18]. These include short range radios like Wi-Fi [23], Zigbee [24], Z-wave [25], Bluetooth [26] - [28]. With advances in the field of IoT technologies, several machine-to-machine (M2M) connectivity protocols have been deployed [29]. Similarly, long range radios like Low Power Long Range Radio (LoRaWAN) [30] or IPv6 over Low Power Personal Area Networks (6LoWPAN) [31] can also achieve M2M connectivity and a data aggregator is typically used to connect to multiple device in the field and relay data back to the cloud. These schemes rely on internet access points (AP), usually in the form of wired (PLC, LAN or fiber-optic) or wireless (cellular, Wi-Fi/WiMAX) transponders.

Authors in [34], have proposed a consumer-centric platform that integrates sensors and communication architecture with the smart grid infrastructure. The platform uses Zigbee and an internet AP while residing in a consumer’s premises. The work does not address how the system can be deployed for other electric distribution applications or how the system can operate in areas of sparse/no connectivity. In [36], authors propose a decentralized control for achieving power flows in distribution networks. With a multi-tier communications and decentralized intelligence, better power flow control and a reduction in data traffic has been achieved. However, the communication network proposed suffers similar drawbacks as mentioned above. Similarly, in [38], authors have proposed a purely simulation based platform for asset management and power flow control, with no practical deployment evidence. In [37], authors propose an ad-hoc network for controlling intelligent energy devices connected to it. Based on system level parameters, the decentralized controller can instruct connected devices to take appropriate actions. In [39], authors have a similar approach with an integrated WiMAX communications layer. Deploying such ‘online’ systems in rural/remote areas would be challenging, since neither Wi-Fi nor wired access points may be available.
Authors in [40], propose a mechanism to connect and read data from isolated smart grid devices, using a Zigbee enabled reader device to bridge the connectivity between the device in the field and the utility cloud. However, the utility has to rely on custom hardware like the reader device, to bridge this ‘last-mile’ connection to the cloud.

An important characteristic of traditional IoT-type solutions can be highlighted here—
Most solutions developed in literature [7] - [31] have relied on the presence of a backhaul infrastructure to connect the AP/gateway device to the cloud. However this is a non-trivial problem while connecting devices in sparsely populated areas where such infrastructure does not exist. Establishing this ‘last-mile connectivity’ is often times expensive and utilities may incur poor ROI (return on investment). Moreover, the assumption breaks down when dealing with remote locations, which is a very common case for electric distribution utilities. Similarly, scaling can also be a major challenge when dealing with a variety of utility assets in the distribution network.

It is evident that existing literature fails to provide low-cost, edge-aware sensing solutions that can work in remote areas and can be cost-effectively deployed at scale, while delivering operational insights to electric utilities.

2.2.2 Edge-Computing Architectures for Smart Grids

The discussion so far suggests advantages for architectures where data and information can be analyzed ‘at the edge’ of the network i.e. a flavour of edge computing. In the traditional sense, edge computing for smart grids has been a popular research area for many years. State-of-the-art edge-computing methods often leverage a hierarchical approach to push the computing task towards elements residing near the edge of the network. The aim of this approach is to significantly reduce data traffic and latency. This in turn promises a faster response time. A hierarchical network architecture to promote edge computing is shown in Fig. 2.5 [41].

It must be noted that the layered, hierarchical models work well within well-established communication infrastructures. In these scenarios, operators can designate specific nodes that have available processing power to be responsible for performing computational tasks. As they are located closer to the edge, the communication round-trip-time is minimized, improving the overall system response time, robustness and latency. However, it does not assume that under some scenarios like loss of communication links or higher latency, ser-
Various smart grid applications using this approach have been studied in literature. In [42], an edge-computing framework for monitoring smart grid assets in real-time has been developed. It has been compared with traditional cloud-based computing and a better system response time has been demonstrated.

Researchers have showcased edge computing applications in the bulk transmission systems as well. For instance, in [43], authors have used advanced sensors like PMUs and their time-series data for detecting transmission line trips. In [45], authors have shown the benefits of edge-computing in surveillance of transmission lines, micro-grid management, and AMI data concentrators through numerical simulations.

In the distribution system, edge computing techniques for home energy management systems (HEMs) have been popular in recent times. These types of solutions help in optimizing a customer-centric goal like minimizing electricity consumption or overall costs by optimally controlling a users appliances or analyzing consumption patterns. The use of historical data along with powerful machine-learning tools like regression, classification, clustering and reinforcement decision making have been exploited to achieve these
goals, while relying on the customers home area network (HAN)— for instance, a home Wi-Fi network or a ZigBee gateway. This concept can be similarly extended into smart meters/AMI-based solutions with advanced functionalities [34], [46] - [52]. Since smart meters already have access to high-resolution waveform data (voltage, current or power) and other parameters (like power factor, real-time price etc.) they can, in principle, be effectively used for analytical purposes like integration with home appliance control [34] or non-intrusive load monitoring (NILM) [46].

Authors in [46, 47] have shown that smart meters can be leveraged as edge computing nodes to perform tasks like demand side management, load identification and abnormality detection. The work has shown the promise of embedded edge computing and in-situ analytics using legacy sensors like smart meters. This unlocks the potential value from analytics at the edge, using neural networks without significant computational complexity. This approach has reduced data uplink requirements by $1000\times$.

Current and power sensors have been utilized to perform advanced functions like load
monitoring (i.e. load dis-aggregation and non-intrusive load monitoring), useful for performing demand response activities [49] or monitoring special types of loads (e.g. EVs—[50]). Instances of waveform analytical tools for classifying distribution grid power disturbances have been demonstrated in literature [48]. However, most of these methods utilize hierarchical communication networks (like the one depicted in Fig. 2.3) or a cloud-computing platform as shown in Fig. 2.7.

![Figure 2.7: Examples of load and waveform analytical methods (a) A NILM platform for building level demand response [49], (b) A waveform analytical tool developed for distribution grids [48].](image)

However, most HEMs or smart meter-based solutions have been demonstrated on very customized hardware platforms like single board computers, or sophisticated data acquisition cards. For instance, the hardware implementation in [46], uses a single board embedded computer, which is customized, expensive, and not designed for solutions at scale.

Smart meters with built-in edge analytics can add a lot of value to utility operations, but are a small sub-set of the existing implementation [52] and suffer from high overall costs because they use dedicated, hierarchical communication networks (pictured in Fig. 2.3 and Fig. 2.5).

A brief summary of various edge-computing nodes proposed in literature has been listed in Table 2.1.
Utilities and researchers have recognized the importance of decentralized and distributed intelligence [53] at the distribution level. While the adoption of feature-rich sensors on transmission systems has been on the rise, the same cannot be said for distribution systems. This is primarily since feature-rich, ‘smart’ sensors are often very expensive and impractical to scale to the millions that are needed in distribution networks.

We can thus conclude that there exists a gap in literature for solutions that utilize sensors with edge computing capabilities for monitoring distribution grid assets.
Table 2.1: Comparison of edge-computing nodes for smart grids proposed in literature

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Network infrastructure-based (Mobile edge computing [54] - [56], PMU data fusion [43])</th>
<th>Microgrid-based [57]</th>
<th>HEMs-based systems [44, 58, 59]</th>
<th>Smart meter-based [34, 46, 51]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processor</td>
<td>Complex processors and virtual machines [54, 55, 56]</td>
<td>64-bit, Quad-core CPU running full Windows-10</td>
<td>64-bit, Quad-core CPU</td>
<td>32-bit ARM–7 MCU [34], Custom single-board computer [46, 51]</td>
</tr>
<tr>
<td>Memory</td>
<td>N/A</td>
<td>64 GB on-board flash</td>
<td>1 GB RAM</td>
<td>128 kB [34], 512 MB [51]</td>
</tr>
<tr>
<td>Communication interfaces</td>
<td>Cellular (4/5–G wireless) [43], generic radios, software-defined networking [54, 55]</td>
<td>Ethernet, Wi-Fi, BLE</td>
<td>Ethernet, BLE</td>
<td>Zigbee gateway</td>
</tr>
<tr>
<td>Peripherals</td>
<td>N/A</td>
<td>GPIOs, HDMI, USB</td>
<td>GPIOs, HDMI, USB</td>
<td>Energy metering</td>
</tr>
<tr>
<td>Criteria</td>
<td>Network infrastructure-based (Mobile edge computing [54] - [56]), PMU data fusion [43])</td>
<td>Microgrid-based [57]</td>
<td>HEMs-based systems [44, 58, 59]</td>
<td>Smart meter-based [34, 46, 51]</td>
</tr>
<tr>
<td>--------------------------------------</td>
<td>------------------------------------------------------------------------------------------</td>
<td>----------------------</td>
<td>-----------------------------</td>
<td>-------------------------------</td>
</tr>
<tr>
<td>Cost</td>
<td>N/A</td>
<td>$300+, only available in small quantities</td>
<td>$35, only available in small quantities</td>
<td>$30 for [34], N/A for [51]</td>
</tr>
<tr>
<td>Applications</td>
<td>Situational awareness using sensor data, optimal charging of EVs, non-intrusive load monitoring</td>
<td>Blockchain based microgrid management, demand response, optimal scheduling of home appliances</td>
<td>Integration with smart home appliances, data access for customers, sensor/actuator integration, load dis-aggregation</td>
<td></td>
</tr>
</tbody>
</table>
2.3 Smart Sensors for the Electric Grid

In this section, we examine some of the work reported for smart sensors for the distribution grid. These include sensors for fundamental electrical quantities like voltage and current, as well as derived quantities like power and energy. For utilities, current sensors are indispensable for monitoring the distribution system and have been used for various instrumentation and sensing applications like smart meters, asset monitors, \( \mu \)-PMUs to obtain more visibility into the grid.

The advent of PMUs has improved the level of visibility and low-latency communication between distant nodes that utilities in the transmission network. With GPS-synchronized timing signal and data acquisition, utilities were able to monitor power flows and stability coefficients for the critical transmission infrastructure. It was also possible to measure the minute phase differences at different points in the network and use those to exert effective control on the state of the system (e.g. power flow control). The same level of visibility and control was envisioned through the introduction of the smart meters and AMI in the distribution network.

When introduced, the AMI system replaced AMR (Automated Meter Reading) systems with the vision that AMI can serve as a platform for distribution automation [17]. However, very few utilities have succeeded in executing this at a low capital and operational cost. This is in part due to the tremendous IT (information technology) migration and customization effort needed to ‘close the loop’ and achieve control capability with existing AMI/AMR infrastructure. Besides, setting up a dedicated backhaul for distribution automation system has been proven to be expensive [15]. Vendors of these smart systems also have to design different solutions for different geographical regions, further adding to the overall costs. Finally, technology migration is forcing updates in 5 – 7 years as opposed to the planned 15 years life-cycle, further calling into question the economic model. This has resulted in utilities struggling to show high value for their AMI investments [136].
The general trend in ‘smart sensors’ literature has been to utilize IoT-like solutions to push data to the cloud and leverage cloud-based analytics to extract additional layers of value from the sensed data. This is a fundamental flaw in status-quo and is discussed in the next few sections.

2.3.1 Current Sensing Solutions for Smart Grids

For the operation and control of the power grid, voltage, current and frequency are important system parameters that need to be measured. Voltage sensing is not very challenging as typically, different points in the power grid have tightly regulated voltages (e.g. in the distribution network primary side, voltage levels are fixed to 7.2, 12.47, 34.5 kV and so forth, while the low voltage secondary network is standardized to 120/240/277 V) and several standardized measurement techniques have emerged. As a result, voltage sensors are universal and consequently, obtaining frequency measurements from voltage measurement is also not very challenging.

On the other hand, current measurement is more complex. At different levels in the power grid, it is important to monitor the current; both steady state as well as faults, flowing through different assets like transformers, capacitor banks, tie-switches, re-closers, section-alizers, VVCs etc. Current sensing techniques [64] can be broadly categorized into—

- Ohm’s law of resistance— These techniques rely on measuring a voltage drop across a series resistive element (typically called a sense resistor) which has a fixed known value. The current is measured by \( i(t) = \frac{v(t)}{R} \). These methods are more suitable for measurement of currents in low-power embedded devices since losses and isolation can be a concern when these techniques are applied to power line voltages and currents.

- Faraday’s law of electromagnetic induction— Faraday’s law states that the rate of
change of flux is equal to the induced EMF, i.e. —

\[ E = -N \frac{d\phi}{dt} \]  

(2.1)

The predominant sensors utilizing this phenomenon are CTs and Rogowski coils. They inherently provide galvanic isolation between the conductor of interest and the sensing sub-system, but can only work on AC systems (i.e. they cannot measure DC currents).

- Utilizing magnetic field sensing — Since all current (AC or DC) carrying conductors produce a magnetic field, the current can be estimated by measuring the magnetic field and knowing the physical geometry of the sensor system with respect to the conductor. The field itself can be measured by different approaches, like Hall effect (when current \( I \) flows through a conductive material that is penetrated by magnetic flux density \( B \), a voltage \( v \) is generated proportional to \( I \) and \( B \)), Flux gate principle (utilizes the non-linear relation between magnetic field \( H \) and flux density \( B \) within a magnetic material), Magneto Resistance effect (change in electrical resistance due to an applied magnetic field) etc.

- Faraday effect — These type of sensors utilize the change in polarization of light due to an external magnetic field. These sensors are used specifically when electrical isolation is crucial (e.g. for transmission sensors) and tend to be expensive.

Reference [64] is an excellent resource, summarizing the different techniques used for current sensing.

For utility applications, operators are interested in time-series current profiles, typically recorded as root-mean-squared (RMS) measurements along with other quantities of interest (like voltages and power flows). CTs are the traditionally preferred solutions by utility operators, since they need minimal signal conditioning, providing a 1 : \( N \) “transformation” of the current, which is converted into a voltage signal by passing it through a
fixed burden resistor ($R_s$ shown in Fig. 2.8(c)). The CTs are sized according to the current being measured, across the expected range of values. The range of measurements any transducer can cover is called dynamic range. It is expressed as a ratio of largest possible measurement possible with a sensor, compared to the smallest possible measurement. For instance, if a sensor’s least count (i.e. smallest recordable measurement) is 1 A and the largest measurement possible with the sensor is 1000 A, then the dynamic range of the sensor can be expressed as 1 : 1000.

Occasionally unforeseen circumstances can cause power disturbances and system faults, triggering switch-gear and protective equipment causing system transients. Rarely this can result in system instabilities, widespread outages and even catastrophic damage to equipment. In these cases, current waveforms can be crucial for determining the root case and performing post-event analysis.

In general, highly specialized, expensive sensors are required for capturing fault currents as they can range from several 100’s of Amperes to several 1000’s of Amperes. Thus, these sensors must possess a high dynamic range. They also need a high-speed signal conditioning and data acquisition stage to avoid any distortions in the waveform being cap-
An important aspect for the feasibility of current sensors is the ability to install them on existing equipment (like conductors) in the field. This ultimately influences the installation complexity and overall cost of the sensor. Current transformers (CTs) cannot be easily installed on any conductors without having to de-energize the system and reconfigure the conductors. Line-technicians often have to sever or disconnect conductors in the field to pass them through the CTs as part of the installation process. This is true for most other applications utilizing CTs and can be a pain point from an installation perspective.

In literature, numerous ‘non-invasive’ current sensors, that can be ‘stuck-on’ or ‘clipped’ around conductors of interest have been proposed and studied. These type of sensors help with quick and easy installation in the field with a sensing modality adopted for the asset being monitored. A brief analysis of these sensor solutions is presented next.

Authors in [65] and [66], have developed a stick-on current sensor for over-head transmission lines. The sensor in [65] uses two wire-wound magnetic pick up coils in open loop configuration for capturing the magnetic flux and measuring the current flowing in the asset of interest. An algorithm running on the sensor helps in discriminating stray flux that causes interference. The method of using pick-up coils or magnetic flux sensors in a pre-determined arrangement has gained popularity with several approaches being proposed recently. The solution in [66] uses a closed-core configuration. Both the sensors harvest

Figure 2.9: Solutions using magnetic flux sensors (a) Stick on sensor for overhead transmission lines [65], (b) Magnetic sensor array for home energy monitoring [67].
energy from the transmission lines. This is done through flux concentrators.

In [67] and [68], a current sensor for monitoring conductors located inside home conduits near the main breaker panel has been proposed. The sensor uses similar multiple magnetic pick-up coils in a 3-D spatial arrangement to record flux from three current carrying conductors in the home wiring system and a computer-based non-linear least squares solver to compute the constituent currents of interest. In [69], a circular arrangement of Hall effect and flux-gate sensors has been analyzed for a comparison between their performances. These sensors are envisioned to be used for both AC and DC current carrying conductors. The work in [74] is targeted towards underground, multi-core cables. In [70], a non-intrusive current sensor for two-wire power cords connected to household appliances has been developed. The research showcases good accuracy and linearity for $0 - 20$ A and utilizes magnetoresistive (GMR) sensors and can be clipped onto the power cord. Authors in [71] have proposed a non-contact current probe based on Hall effect and GMR sensors in a fixed geometry. The probe can be used in places where $360^\circ$ access to the current carrying conductor is not possible, and can thus work in a limited space. With advances in 3-D printing and manufacturing capabilities, direct wire printing of flexible CTs with magnetic cores has been demonstrated in [72]. The solution is targeted towards indoor use, specially for building energy management.

A major drawback of this approach is the use of magnetic (ferrous) material that can saturate at high currents (e.g. in a fault scenario) and cause non-linear behaviour in the
sensor and measurement errors.

With a rapid proliferation of IoT-based technology and dropping prices of wireless radio and “connected” microcontroller (MCU) solutions, numerous IoT-based current sensors have been recently proposed. Zigbee and Bluetooth are popular low-cost wireless networking protocols that can be implemented on low-power MCUs. This allows the current sensors to “push” recorded data points to a remote datalogging system for real-time data acquisition. In [75], a Zigbee-based electronic CT has been proposed, using Hall-effect sensors. The device can be clipped around conductors of interest and can reconstruct waveforms accurately. In [76], a Bluetooth based, self-powered current monitoring solution for sub-station cables has been developed. The sensor uses Hall effect transducers in open loop configuration to measure current, along with a voltage drop measurement and temperature sensor to estimate the electrical contact resistance of the conductor. In [77], a magneto-resistance-based chip is used. These solutions use measurements reported to a data collector unit through a gateway on the premises and further analysis is done on a computer-based system.

![Examples of Hall-effect based current sensors](image)

**Figure 2.11:** Examples of Hall-effect based current sensors (a) Circular arrangement of Hall effect and GMR sensors [69], (b) Coreless current probe for conductors with reduced access [71], (c) Bluetooth-based smart connector [76].

Several commercial sensors for power grid monitoring have been developed with the aim of gaining advanced visibility into the transmission and distribution networks. For instance, [79] and [78] are clamp-on sensors for overhead power lines that can measure load current and power quality disturbances. They report these data periodically (every 15 min) to the utility head end system through cellular, Wi-Fi or private links, which are
expensive to establish in arbitrary locations.

Figure 2.12: Examples of commercial transmission line current sensors (a) Line Sentry by Grid Sentry LLC [78], (b) Gridsense LineIQ by FranklinGrid [79].

The solutions discussed so far have specific advantages when considering ease of use and installation, immunity to interference, etc. However, many of the sensing methods [65, 67, 69] inherently cannot capture the individual current waveform, but rather provide an average (or RMS) current level in the conductor. This can be a limitation if a utility operator is interested in the occasional waveform snapshot for diagnostic purposes.

A majority of the proposed sensors have been designed for specific geometries— for instance, [65] works for overhead transmission lines with a minimum separation between two adjacent conductors, while [67, 70] have been designed for multi-conductor configurations. Moreover, a majority of the proposed sensors utilize magnetic coils or Hall effect transducers. These transducers exhibit linear response over a fixed range. Since they often use ferrous material for magnetic flux concentration, the sensors tend to saturate when op-

Figure 2.13: Fault current waveform and associated CT saturation [81].

32
rated in conditions where the magnetic flux is high. This means that the *dynamic range of the sensors based on the methods discussed so far is limited*. This limitation adds a layer of complexity when configuring sensors for different current levels and they cannot be used for fault current sensing. CTs, which have been the most popular, widely used current sensing alternative also suffer from the same drawback—non-linear response beyond rated currents [81] as seen in Fig. 2.13. This non-linearity heavily distorts the waveform being acquired during fault transients, making the acquired waveform not very useful for post-fault diagnostics.

![Figure 2.14: Examples of waveform distortion caused due to current sensor limitations: Event ID #21852, #21831 and #21839 in [82]. Highly customized ‘smart sensors’ are needed for advanced distribution grid visibility.](image)

In fact, a popularly used fault disturbance library has recorded several such fault inci-
dences, but the waveforms being captured have saturated the ferrous cores of the CTs, and as a result, the waveforms have been heavily distorted. A few of these instances have been illustrated in Fig. 2.14.

A critical comparison of state-of-the-art ‘smart current sensors’, from the point of view of communication infrastructure requirements, integrated analytics and installation effort has been presented in Table 2.2.
### Table 2.2: Smart current sensors proposed in literature

<table>
<thead>
<tr>
<th>Reference</th>
<th>Communication</th>
<th>Fault capture</th>
<th>Integrated analytics</th>
<th>Installation effort</th>
</tr>
</thead>
<tbody>
<tr>
<td>[65], [66]</td>
<td>Zigbee [65, 66] links to centralized terminals</td>
<td>No</td>
<td>No</td>
<td>Low for [65], High for [66]</td>
</tr>
<tr>
<td>[75], [76], [77]</td>
<td>Zigbee [75] &amp; Bluetooth [76], [77] links to centralized terminals</td>
<td>Yes for [75], No for [76, 77]</td>
<td>No</td>
<td>Low for [75, 76], High for [77]</td>
</tr>
<tr>
<td>[78], [79], [80]</td>
<td>Cellular, Wi-Fi, satellite links to centralized terminals</td>
<td>Yes</td>
<td>No</td>
<td>High for [78], [80]; Low for [79]</td>
</tr>
<tr>
<td>[69], [74]</td>
<td>Wired to computer for analysis</td>
<td>No</td>
<td>No</td>
<td>High</td>
</tr>
<tr>
<td>[67], [68], [71], [72]</td>
<td>Wired to computer for [67], 433 MHz RF for [68] and LoRaWAN for [72] links to centralized terminals</td>
<td>No</td>
<td>No</td>
<td>High for [67] and [68], Low for [72] and [71]</td>
</tr>
</tbody>
</table>

Above discussion highlights drawbacks of current sensors that have been proposed in literature. Most of the techniques are expensive and do not scale well in the distribution system. Many magnetic field based sensors are tailored for specific geometries only. These can be difficult to adapt to the requirements presented by arbitrary conductors in the field. Some methods like Hall effect sensors, or magneto-resistive sensors are not suitable for utility applications due to complex signal conditioning requirements [64].

In general, we need current sensors that—

1. Are inexpensive and can be quickly and easily installed on conductors in the field

2. Have high dynamic range and can capture very large as well as small currents without significant measurement errors

3. Can capture waveforms on demand
4. Can extract features of interest (e.g. harmonics, distortions, etc.) from the data being captured—i.e. acts as a smart sensor with edge computing capability

5. Can function without needing constant communication with the cloud so that it can be deployed in remote areas in the distribution network

Based on the different current sensing methods discussed so far, Rogowski coil current sensors exhibit a very high dynamic range, can capture waveforms and can be easily installed in the field. These are examined next.
2.3.2 Rogowski Coil Current Sensors

Rogowski coils are popular in the power industry and excellent transducers for measuring both alternating and pulsed currents, which exhibit an inherent \( \frac{di}{dt} \) [83] - [86]. Rogowski coils exhibit several advantages over current transformers (CTs) and other magnetic effect sensors like Hall effect or even shunt-based current transducers. Rogowski coils are air-cored, and hence cannot saturate due to the absence of magnetic (ferrous) elements. A high bandwidth can be achieved, along with a linear response [87] over a wide dynamic range, compared to CTs with magnetic cores. Rogowski coils are also resilient to thermal, conducted and radiated noise [88] - [91]. Additionally, they offer galvanic isolation, which is essential when measuring power line currents.

Table 2.3: Comparison of Rogowski coils with other current sensing techniques

<table>
<thead>
<tr>
<th>Feature</th>
<th>Rogowski coil</th>
<th>CTs</th>
<th>Hall effect sensors</th>
<th>Magnetic Field Sensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electrical isolation</td>
<td>Available</td>
<td>Available</td>
<td>Available</td>
<td>Available</td>
</tr>
<tr>
<td>Signal conditioning stage</td>
<td>Minimal (integrator)</td>
<td>Minimal (burden)</td>
<td>Complex</td>
<td>Complex</td>
</tr>
<tr>
<td>Waveform information</td>
<td>Available</td>
<td>Available</td>
<td>Available</td>
<td>Generally not available</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>High (several MHz possible)</td>
<td>Low</td>
<td>Moderate</td>
<td>Moderate</td>
</tr>
<tr>
<td>Dynamic range</td>
<td>Very high</td>
<td>Moderate (magnetic saturation exists)</td>
<td>Moderate (magnetic saturation exists)</td>
<td>Moderate (magnetic saturation exists)</td>
</tr>
<tr>
<td>Immunity from external EMI</td>
<td>Generally immune</td>
<td>Immune</td>
<td>Need special circuits or arrangements to eliminate EMI</td>
<td>Need special circuits or arrangements to eliminate EMI</td>
</tr>
<tr>
<td>Cost</td>
<td>Low</td>
<td>Low</td>
<td>Moderate</td>
<td>High</td>
</tr>
</tbody>
</table>
In power systems, Rogowski coils have been used for protective relaying applications and metering. However, they are less predominant than CTs primarily because the signal conditioning circuits required for Rogowski coils are more complex than those required for CTs. Since Rogowski coils are $di/dt$ sensors, they produce a voltage signal that is proportional to the current enclosed by the coil. In order to reconstruct and measure the current, the voltage signal is integrated either through an analog integrator or through a digital (DSP) based system. However, Rogowski coil signal conditioning stages are relatively less complicated as compared to most other current sensing techniques discussed so far [64], making them ideal for power electronics and power system applications. Compared
to Rogowski coils, CTs can be bulky and expensive [84], especially as the current rating increases, due to the core requirements.

The recent advances in manufacturing techniques have helped designers in integrating the toroidal windings on printed circuit boards (PCBs), thus achieving a compact form-factor, low cost and good reproducibility [99] - [105]. Besides, the availability of precision-trimmed operational amplifiers (op-amps) has helped in achieving low drift, fast settling analog (active) integrator circuits. Analog integrators can condition the signals from the Rogowski coil and feed them into a data converter and micro-processor based unit that can record the data or perform certain control actions based on it. PCB-based Rogowski coils have been developed for both power-line frequencies [102] - [110] (50/60 Hz) as well as switched mode power converters [99].

A comprehensive survey of ~ 20 papers related to Rogowski coil sensors was carried out. A comparison with respect to their bandwidth, form factor, dynamic range and applications has been shown in Table 2.4.
<table>
<thead>
<tr>
<th>Reference</th>
<th>Bandwidth</th>
<th>Size</th>
<th>Dynamic Range</th>
<th>Applications</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>[93]</td>
<td>50 Hz - 800 Hz</td>
<td>18 cm²</td>
<td>1 to 100</td>
<td>Power frequency applications</td>
<td>Square Rogowski coil, for fault diagnosis of on-line load tap changer in aerospace power systems</td>
</tr>
<tr>
<td>[95] &amp; [127]</td>
<td>10 Hz - 400 Hz for [95] &amp; 1 Hz - 150 Hz for [127]</td>
<td>[95] 55 cm² &amp; [127] 50 cm²</td>
<td>[95] 1 to 2000 &amp; [127] 1 to 300</td>
<td>Motor fault or condition monitoring in machines (50/60 Hz)</td>
<td>Not actually PCB-embedded, but wire-wound</td>
</tr>
<tr>
<td>[99] &amp; [100]</td>
<td>500 Hz - 1 MHz</td>
<td>&lt; 7 cm²</td>
<td>1 to 5000</td>
<td>Embedded in power converter gate-drive for protection of switches</td>
<td>Integrator &amp; comparator specifically designed to trigger a ‘shutdown’ pulse when over-current condition detected</td>
</tr>
<tr>
<td>[101]</td>
<td>100 Hz - 1 MHz</td>
<td>N/A</td>
<td>~ 1 to 700</td>
<td>Measuring high $di/dt$ pulsed currents in lasers</td>
<td>PC based system, mainly designed for high currents, of the order of several kA</td>
</tr>
</tbody>
</table>
Table 2.4 continued

<table>
<thead>
<tr>
<th>Reference</th>
<th>Bandwidth</th>
<th>Size</th>
<th>Dynamic Range</th>
<th>Applications</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>[102]</td>
<td>DC - 1 MHz</td>
<td>N/A</td>
<td>1 to 500</td>
<td>Power line frequencies as well as switching power converters</td>
<td>No active integrator used, output saturates beyond 500 A</td>
</tr>
<tr>
<td>[103]</td>
<td>60 Hz</td>
<td>Volume of 295 cm³</td>
<td>1 to 72</td>
<td>Measuring power line currents</td>
<td>A method to mass-produce a Rogowski coils based on an assembly of 2 PCBs, which is a complex assembly</td>
</tr>
<tr>
<td>[107] &amp; [108]</td>
<td>50 Hz - 700 kHz</td>
<td>N/A</td>
<td>1 to 190,000</td>
<td>Protective relaying for power line applications</td>
<td>2 PCB coils wound in opposite directions, passive integrator</td>
</tr>
<tr>
<td>[112]</td>
<td>20 MHz</td>
<td>0.64 cm² for coil</td>
<td>N/A</td>
<td>Switching converters in EVs</td>
<td>4-layered PCB, differential Rogowski coil design to eliminate common mode $dv/dt$ coupling</td>
</tr>
<tr>
<td>Reference</td>
<td>Bandwidth</td>
<td>Size</td>
<td>Dynamic Range</td>
<td>Applications</td>
<td>Notes</td>
</tr>
<tr>
<td>-----------</td>
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<td>---------------</td>
<td>------------------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------</td>
</tr>
<tr>
<td>[114]</td>
<td>10 Hz - 1 MHz</td>
<td>6.6 cm² for coil</td>
<td>N/A</td>
<td>DC link capacitor currents in 20 kHz buck converter</td>
<td>Active integrator used till 1 MHz and self-integrating coil recommended for $f &gt; 1$ MHz</td>
</tr>
<tr>
<td>[113] &amp; [126]</td>
<td>[113] 10 MHz - 175 MHz</td>
<td>[113] 314 cm² &amp; [126] 515 cm²</td>
<td>[113] 1 to 5000 &amp; [126] 1 to 40</td>
<td>For high currents (upper limit of 100 kA) &amp; a rise time of several nanoseconds</td>
<td>Wire wound on a PCB, self integrating coil</td>
</tr>
<tr>
<td>[121]</td>
<td>0.01 Hz - 43 kHz</td>
<td>51 cm² for coil</td>
<td>1 to 11</td>
<td>Transient &amp; fault current capture for overhead transmission lines</td>
<td>Pair of differential coils used, only high frequency components (&gt; 1 kHz) &amp; impulses captured (&gt; 1000 A)</td>
</tr>
<tr>
<td>[122]</td>
<td>N/A</td>
<td>N/A</td>
<td>1 to 5000</td>
<td>Gas-insulated switchgear in HV power line applications</td>
<td>Active integrator</td>
</tr>
<tr>
<td>Reference</td>
<td>Bandwidth</td>
<td>Size</td>
<td>Dynamic Range</td>
<td>Applications</td>
<td>Notes</td>
</tr>
<tr>
<td>-----------</td>
<td>----------------</td>
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<td>----------------------------------------------------------------------</td>
</tr>
<tr>
<td>[123]</td>
<td>50 Hz - 50 kHz</td>
<td>69 cm²</td>
<td>1 to 300</td>
<td>Power frequency applications (50/60 Hz)</td>
<td>High density interconnect PCB based coils, using a complex assembly of coils to construct a sensor that is resistant to external EMI</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[124]</td>
<td>60 Hz - 1.2 kHz</td>
<td>240 cm²</td>
<td>1 to 75</td>
<td>Capturingtransients in industrial processes like welding and circuit breaker testing</td>
<td>Machinable Rogowski Coils (MRCs) based on a custom wire-wound design</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[119]</td>
<td>50 Hz</td>
<td>1360 cm²</td>
<td>N/A</td>
<td>Current measurement in furnaces, ranging to ∼ 300 kA. Main conductor split into 8 branches.</td>
<td>A complex PCB-based structure containing 8 Rogowski coils built and tested till 12 kA.</td>
</tr>
</tbody>
</table>
We can see that there are certain limitations that could be improved. The dynamic range of Rogowski coils is limited by the signal conditioning circuitry. Even though Rogowski coils (air-cored, non-ferrous) themselves do not saturate and offer much higher dynamic range than the magnetic core based CTs (that can saturate), the primary limitation is the signal conditioning circuit. For instance, typical CTs exhibit dynamic ranges up to $1 : 5000$, while Rogowski coils show linear behaviour over a much larger range. In fact, the coil itself can linearly produce voltages proportional to the $\frac{di}{dt}$ in the current carrying conductor. However, the active integrator based signal conditioning stage can have a limited dynamic range.

These stages are generally built using op-amps and start saturating (causing signal distortion and clipping) when the signal levels approach the supply rail voltages. Rogowski coil sensor with a static integrator gain, will thus exhibit a limited dynamic range that is dictated by these rail voltages.

Further, the analog signal is interfaced with an analog-front end (AFE) or an analog to digital converter (ADC), that typically accepts signals between 0 and $+5$ V. This sets an upper limit on the dynamic range that can be achieved. These active integrator circuits can also add some phase shift in the signal, which can add to significant errors when the signal is used for power metering or for operating protection equipment [84].

Another major drawback for Rogowski coils, when considering their application in the power domain is the fact that the coils have to encircle the conductor when measuring currents. This drawback is similar to the problem presented by CTs— the utility technicians have to disconnect the cables before installing the sensors and this can be challenging when considering the overall cost. Thus retrofit capability is important for a low cost, commercially viable design. While several designs have been proposed [115], the solutions are still significantly expensive ($> 150$). Thus, while the need for ubiquitous sensing is well recognized, it is economically challenging to justify a widespread deployment, often limiting it to high value applications in the transmission and sub-transmission systems.
While clip-on current sensing solutions using both magnetic and Rogowski principles exist, their dynamic range is insufficient to cover a wide range of current levels, including steady state and fault currents. A single sensor, that can intelligently scale itself and ‘auto-tune’ to the current levels being measured at a low-cost can help in justifying ubiquitous sensing, providing value to the utility operations. It would then be able to capture both steady state currents (10’s to 100’s of Amperes) and fault current profiles (several 10’s of kilo-Amperes) in a single package, while intelligently adapting to both operating points.

2.3.3 Asset Monitoring Applications in Distribution Networks

As discussed previously, a major transformation is underway in the electric distribution network, that is adding unprecedented stress on the aging distribution infrastructure. The utility assets like transformers, OLTCs, reclosers etc. that were designed for 20+ years of operation, are experiencing sudden and untimely failures due to the impact of DERs. There is a sharp contrast in the asset monitoring techniques that have been implemented for generation, transmission and sub-transmission networks, compared to what can work in the distribution grid.

Critical grid infrastructure like large power transformers (LPTs) (50+ MW) in generation and sub-station premises are heavily monitored and instrumented using several state-of-the-art methods [128]. There are several research areas documenting failure modes of these LPTs ranging from dissolved gas analysis, frequency response methods, turns ratio tests, degree of polymerization test, online monitoring of top oil temperature, or electrical and acoustic methods for partial discharge detection to name a few. Since these LPTs are often located in premises, in controlled environments where several parameters can be closely monitored, without concerns for costs pertaining to the sensors, the data acquisition stages or communication systems. Moreover, these methods can be ‘offline’ in nature, where periodically the asset can be switched out or decommissioned for health monitoring purposes and commissioned back when the tests are completed.
On the other hand, consider the most common utility distribution system asset— the service transformer. A typical North American mid-sized utility serving more than 3 million customers would have 400,000 to 500,000 pole-mounted transformers in the field. A single transformer can cost around $1,000 – $2,000. There are several commercially available products for monitoring the health of pole-top transformers [140] with costs ranging from $600 – $1500. On top of the sensor costs, there are costs associated with installing, operating and commissioning the large fleet of sensors reporting granular data to the cloud. The total solution ends up becoming as expensive as the transformer being monitored, and as a result, utilities are unable to justify the ROI while considering the deployment of these type of sensor networks. Thus, utilities often revert to a ‘run-to-failure’ approach, where pole-top transformers are operated blindly, until a problem is encountered. If an asset fails in the field, a trouble crew is sent out to assess the situation and replace the transformer if required. However, with more than 50 million distribution transformers, the overall loss of revenue from transformer failures, unplanned outages and the loss due to inability to

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2 Data obtained through discussions with CDE utility partners
meet SAIDI/SAIFI performance incentives is significant [129]. This creates an opportunity for savings through proactive condition based maintenance. For instance, Commonwealth Edison\(^3\) faces 2,000 distribution transformer failures every year[131], while Hydro Quebec\(^4\) replaces 3,000 transformers annually [129]. In other countries, specially emerging economies, distribution utilities have reported high losses due to premature failures of distribution transformers. For instance, in India, a failure rate of more than 15\% has been reported in literature [130]. Thus, this problem is significant and challenging utilities around the world.

Currently, AMI smart meters are the most widely deployed grid-edge sensors which have vastly improved utility’s visibility, especially into secondary distribution networks. With time-stamped, granular voltage, and power data, AMI has enabled numerous high-value operational and planning capabilities beyond consumer billing [132] such as outage management, load forecasting, topology and phase identification, rooftop PV and EV detection, load dis-aggregation [50] etc. Recent works have also focused on using AMI data for monitoring transformer loading and estimating other parameters [133, 134]. A commonly utilized approach is based on thermal modelling for oil-filled transformers based on the IEEE C57.91 − 2011 standard [135]. These equations take into consideration the overall loading on the transformer and ambient temperature to estimate the internal hotspot temperature. The goal is to maintain the hotspot temperature within certain bounds to prevent accelerated degradation or “aging” of the transformer. The aggregated loading on the transformer can be obtained through downstream AMI data. However, this approach does not take into consideration other sensing modes that can be leveraged to determine the health and performance of distribution transformers— asset specific parameters like asset temperature, geo-locations, mechanical vibrations [151, 128], number of faults the asset experiences etc. These parameters can indicate different aspects of an asset’s degradation cycle.

\(^3\)A large electric utility serving Mid-Western USA

\(^4\)A Canadian public electric utility
Moreover, AMI based technology has a high cost; upwards of $300 per end-point, in addition to installation and communication costs, which can significantly inhibit wide adoption of AMI. In 2016, only 47% of the 152 million electricity customers had smart meters with only 1,372 out of the 2,344 utilities in the U.S. using AMI in their distribution systems. As of 2019, this number has risen to approximately 60% of the total 157 million customers across the U.S. [137]. Of the utilities using AMI, a very small percentage was using it for asset monitoring and doing advanced distribution system management functions. Some of the challenges and utility pain points included high deployment costs, upgrades required to the communication infrastructure and system integration [136].

Utilities have also been able to leverage smart meters and AMI infrastructure to develop custom solutions for grid asset monitoring. For instance, Southern Company\(^5\) customized a smart meter to be installed on a pole-top for monitoring capacitor banks at 9,000 locations\(^6\) across their service territory (refer Fig. 2.17). However, these type of solutions are highly customized and require tedious field engineering\(^7\) and IT manipulation to get the entire solution integrated into the utility operations.

The increasing adoption of distributed energy resources (DERs) like roof-top PV inverters and EVs have increased the stresses imposed on utility assets. This has severely

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\(^5\) A large electric utility serving the South Eastern region of USA
\(^6\) 6,000 in Georgia Power territory and 3,000 in Alabama Power territory
\(^7\) Note that most CTs require conductors to be cut in the field before being installed
affects the useful life of transformers (usually $> 25 – 30$ years) leading to untimely and catastrophic failures.

The most common distribution transformer degradation mechanism is through insulation degradation [162], leading to internal hot-spots and partial discharges. An accelerator for this phenomenon is the continuous overloading of the transformer.

Research has shown that distribution transformers are consistently loaded to more than their rated capacity in the distribution networks as seen in Fig. 2.18. Authors in [157] have studied a city-wide dataset to conclude that only 72% of the transformers in the city service a peak load of less than 90% utilization over the course of one year. Further, 21% of the transformers are heavily utilized ($90 – 125\%$) and experience a peak load of up to
125% of their nameplate capacity. Around 4% of the transformers were overloaded to more than 125% peak loading and another 2% experienced critical overloading, exceeding 150% of their rating. Similarly, a recent study [158] has shown that the uncontrolled charging of EVs, can have a severe detrimental impact on the life of distribution transformers. Even at a 10% penetration the expected life of a 50 kVA transformer can be reduced by up to 20%. Harmonics due to newer, power electronics-based loads and inverters have also contributed to the asset degradation over time [163].

EVs are not the only loads that can cause unforeseen overloading on the distribution transformers. Electric tank-less water heaters can be commonly installed without utility knowledge and can appear as abrupt load fluctuations on the service transformers. For instance, typical water heaters have ratings from 12 kW up to 36 kW depending on vendors. A sample power cycle for the tankless water heater is shown in Fig. 2.20 [160]. If installed on smaller distribution service transformers (e.g. 25 kVA), these loads can cause serious voltage and overloading problems for the connection.

The degradation process is further exacerbated by the number of faults that assets like

![Figure 2.20: Abrupt step power changes in (noted by B and C) and rapid power fluctuations (seen in F, H) [160].](image)
transformers or capacitor banks experience in the field—Fault currents cause excessive heating and momentary mechanical shocks which can cause internal damage to the insulation over time. Eventually this causes degradation of the transformer and early failures.

The issue of transformer overloading is also echoed through utility data. As of 2018, Dominion Energy [161] operated close to 60,724 distribution transformers, out of which 43% were single-phase, pole-top transformers, with 75% serving only residential customers. Amongst the single-phase, pole-top transformers, 25 and 50 kVA nameplate rating was the most common type.

During peak periods, a significant portion of the transformer population was loaded beyond their nameplate ratings. Even the sub-set of residential banks (close to 40,000 transformers) have significant peak time overloading\(^8\) issues reported, sometimes being loaded beyond the peak capability of the transformer\(^9\).

For monitoring distribution transformers, few approaches have been proposed in literature. However, these methods are derivative of those used for condition monitoring of LPTs, relying on intrusive and complex sensing methodology, which may not be suitable for the millions of low-cost assets in the field.

For instance, two commercially available solutions are shown in Fig. 2.21. Pictured in Fig. 2.21(a) is a transformer retrofitted with four sensors for oil-level monitoring [139]. This type of installation can be intrusive and drive up the costs due to complicated field installation procedures. This approach may not scale well when applied to all the distribution transformers in a region, which is a significant population.

Shown in Fig. 2.21(b), is a solution tailored for pole-top service transformer monitoring [140]. This solution relies on a cellular network to communicate with a central cloud server and complex field configuration.

In fact, both the solutions pictured in Fig. 2.21 require a dedicated wireless access point for cloud connectivity. The former needs a router in the field, while the latter uses

---

\(^8\)Ratio of peak load (kW) divided by transformers nameplate (kVA) rating

\(^9\)For single-phase, pole & pad-mount transformers, this factor chosen by most utilities is 125%
cellular modems for internet connectivity. These incur monthly usage costs and are generally expensive in terms of hardware, power requirement, certifications etc.

As discussed, these methods are derived from asset monitoring techniques used for monitoring LPTs in controlled environments like sub-stations or in the transmission networks. Since the assets themselves are very different—LPTs are critical assets and fewer in number, while individual service transformers are less valuable from a system perspective, but are significantly higher in population; the same approaches for asset monitoring cannot justify comparable ROI. This is a challenge with existing approaches for asset monitoring in distribution systems.

This gap in literature is further explored—A few existing solutions for transformer monitoring are summarized and compared in Table 2.5.
Table 2.5: Transformer sensor solutions found in literature

<table>
<thead>
<tr>
<th>Solution</th>
<th>Image</th>
<th>Description</th>
<th>Issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soft sensors for distribution transformers [141]</td>
<td><img src="image1.png" alt="Image" /></td>
<td>Non-intrusive sensors for coupling thermo-electrical models with smart meters.</td>
<td>Cellular or Wi-Fi access point required for getting data back to the cloud.</td>
</tr>
<tr>
<td>Advanced distribution transformer load monitoring [142]</td>
<td><img src="image2.png" alt="Image" /></td>
<td>Sensor that monitors pole-top transformer loading, demonstrated in five locations in Thailand.</td>
<td>Uses 433 MHz custom RF network, along with a GSM based backhaul.</td>
</tr>
<tr>
<td>Self-powered RFID sensors [143]</td>
<td><img src="image3.png" alt="Image" /></td>
<td>Self-powered vibrational sensors.</td>
<td>Solution uses RFID, and needs a customized backhaul to push data to the cloud.</td>
</tr>
<tr>
<td>Embedded Optical Sensing System [144]</td>
<td><img src="image4.png" alt="Image" /></td>
<td>Fiber-optic sensors embedded into distribution transformers for monitoring vibration, temperature and corrosion.</td>
<td>The solution can get complicated for retro-fitting in the field. Wireless modem (AP) required for backhaul communication with the cloud.</td>
</tr>
<tr>
<td><strong>Solution</strong></td>
<td><strong>Image</strong></td>
<td><strong>Description</strong></td>
<td><strong>Issues</strong></td>
</tr>
<tr>
<td>--------------</td>
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</tr>
<tr>
<td>Distribution service transformer health assessment using real-time energy monitor [145]</td>
<td><img src="image1.png" alt="Image" /></td>
<td>Online real-time energy monitoring device reports data to the cloud where fuzzy-logic approach determines health index of each transformer.</td>
<td>Uses traditional IoT-based approach, does not address how the solution can work in areas where communication infrastructure does not exist.</td>
</tr>
<tr>
<td>Wireless PD detection system [146]</td>
<td><img src="image2.png" alt="Image" /></td>
<td>A special wide-band antenna senses PD pulses from a distance. Fast, non-contact approach.</td>
<td>Data relayed to a PC via ethernet or Wi-Fi links, which makes ubiquitous sensing challenging. Only relevant to failure modes that can be picked up by PD measurements.</td>
</tr>
<tr>
<td>Harmonic PMU and Fuzzy-Logic [147]</td>
<td><img src="image3.png" alt="Image" /></td>
<td>Online method for determining inter-turn shorts using fuzzy logic and harmonic, PMU-based measurements on $v(t)$ and $i(t)$ signals.</td>
<td>PMUs are very expensive as they provide synchronized measurements. Proposed method uses terminal measurements on both HV and LV side, which can be challenging.</td>
</tr>
<tr>
<td>Solution</td>
<td>Image</td>
<td>Description</td>
<td>Issues</td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
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<td>-----------------------------------------------------------------------------</td>
<td>------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Transformer protection based on thermal loading [148]</td>
<td><img src="image1.png" alt="Transformer" /></td>
<td>Thermal loading and contingency mitigation for power transformers using IEEE C57.91 – 1995 std.</td>
<td>No information about integrated sensing. Protective relays are expensive and need custom communication network.</td>
</tr>
<tr>
<td>Smart transformers [149]</td>
<td><img src="image2.png" alt="Smart Transformers" /></td>
<td>High frequency CTs used for detecting PDs along with signal processing for online condition monitoring.</td>
<td>Expensive as it uses a customized DAQ and PD measurement system. Needs a custom communication network.</td>
</tr>
<tr>
<td>Fuzzy logic approach for transformer management [150]</td>
<td><img src="image3.png" alt="Fuzzy Logic" /></td>
<td>Data driven approach for real-time, online condition monitoring of power transformers.</td>
<td>Purely data-driven approach, no information regarding actual sensing hardware provided.</td>
</tr>
</tbody>
</table>
A few other model-based and experimental techniques have been reported in literature. Authors in [152] have shown a fault-detection scheme using a terminal measurement-based transformer modeling technique. In a related literature reference [153], an experimental setup to verify the model and inter-turn fault detection method has been discussed, shown in Fig. 2.22. In [154], a method based on Raspberry-Pi interfaced with complex sensing modalities like top-oil sensors has been demonstrated. An online computational engine is used for extracting health-index of the transformer. These methods can be uneconomical to scale to millions of end-points that are needed for monitoring distribution transformers. Evidence regarding field trials, weather-proofing and practical implementation is warranted. Moreover, these ‘online’ methods rely on an internet AP to report these abnormalities to the cloud in real time. Single board computers like Raspberry-Pi require significant power and customization to be deployed in the field.

In conclusion, the major drawbacks for methods described in literature can be summarized as—

- The solutions rely on expensive sensing and instrumentation techniques.
- The solutions require a dedicated backhaul networks (like Wi-Fi/cellular/custom ra-
dios) to push data back to the cloud to be processed.

- The methods result in high installation, customization and operational costs and these solutions fail to scale in an economical way.

Currently, very few solutions exist that can provide decentralized sensing, computation and situational awareness, and have traditionally struggled to be economically viable.

To understand the cause of transformer failures, it is necessary to measure downstream loads. EVs, reverse power flow due to PVs, increased harmonics cause stresses on the transformer, eventually causing it to fail. Of all the causes of failures, the most prominent one is increased number of faults that the transformer experiences in its life time. While the sensors mentioned in [139] - [154] can monitor different parameters like thermal stress and electrical loading, none of them are capable of capturing fault currents or quantifying their impact on the transformer’s overall health. The ability to do so, can provide significant operational advantages for a fleet of distributed assets.

A fundamentally missing piece is a low-cost sensor system that can intelligently monitor different parameters of the transformer, while being non-intrusive in sensing modality, and then interpret the information to provide guidance on asset health. The sensor must function autonomously, at the edge of the network (electrical and communication), and only report the actionable insights to the cloud, through a flexible, low-cost communication infrastructure. Edge computing can be leveraged to process maximum data on the sensor itself and extract meaningful insights, while cloud computing can be used to monitor overall trends and update set points on the sensors. A sensor system for asset management becomes economically feasible viable only if it costs a fraction of the cost of the asset itself. Otherwise, it becomes difficult for the utility to justify the ROI behind the sensor’s deployment.
2.4 Desired Attributes for a Low-Cost Scalable, Decentralized Smart Sensor Network for Distribution Grids

The above discussion highlights some of the requirements behind smart sensor networks for a decentralized grid of the future. These attributes are seen to be quite distinct from typical IoT solutions used for home automation, industrial applications and energy [18], which are generally focused on collecting low-bandwidth information from low-cost sensors, and transferring this information to the cloud— often using dedicated, defined internet APs. The information is processed in the cloud (often on utility premises), allowing feedback loops to be closed at some time in the future, subject to the criticality of the application.

However, the sensing solutions needed for typical applications in the distribution network have to operate in rural areas with poor/no connectivity. They sometimes have to operate with sub-cycle response times to capture power disturbances or to autonomously react to local events. Customization of the solution needs to be minimized to keep the solutions low-cost.

In this regard, some of the desirable features of an ideal sensor system for distribution networks can be listed as—

- **Ultra-low cost and scalability:** Assets in distribution networks can number in millions. The infrastructure (hardware, communication, cloud etc.) should be able to scale rapidly. The cost of each device (unit cost) and the cost of connecting the device to the cloud (communication costs) should be minimal. The communication platform should likewise be able to scale, keeping the operational costs low.

- **Rapid installation in the field:** For electric utilities, the time taken to install a device adds to the overall cost of the solution. Installation times for devices should be minimal. Plug and play devices should be designed.

- **Minimal Customization:** Solutions that cover a wide range of operational points are
desired. Each solution must need minimal or no customization (including hardware customization in the field/software customization for setting up cloud/backend infrastructure etc.), allowing the same sensors to be used in a flexible manner.

- **Autonomous end nodes:** Distributed devices must be able to function (sense, compute, control) autonomously, according to a set of configurable rules that achieve a global objective.

- **Smart end nodes:** Each end node must possess the ability to sense local conditions and the ability to compute and extract features, to make decisions locally. These could act at varying time-scales like sub-cycle transient responses to responses over several days. The response could range from a sensory response (i.e. generating data) or an actuation (i.e. control) response.

- **Flexible communication architecture:** Each end node must function without constant inputs from the cloud. End nodes must be able to work with latencies ranging from several milliseconds to several days. On the other hand, for critical applications, it should be possible to use these sensors with continuous, real-time communication systems.

- **Local data storage:** In order to operate autonomously over varying latencies, the devices need local memory where time-stamped information can be stored before being uplinked to the cloud.

- **Accessibility in remote areas:** The communication system should be operational in remote areas without large infrastructure requirements.

- **Global compatibility and immunity to geographical constraints:** Devices must be immune to large climatic and regulatory variations (like R.F. certifications per country) that are associated with each location or country.
• **Immunity to backhaul technology migration**: With evolving wireless and networking standards, the platform and sensors should not become obsolete.

• **Cybersecurity**: Each end devices must be cybersecure by design. This includes cyber security and cyber-physical security. The cybersecurity architecture should be acceptable for utility applications.

• **Low Energy Budget**: Many end devices could be constrained in terms of available energy. The end nodes must consume minimal power and should be able to operate with energy harvesting and have the power conditioning modules integrated in.

• **Long Life**: End devices and the platform must be designed to have a life span comparable to electric utility assets (25+ years).

In summary, the work reviewed in this chapter fails to satisfy at least one of the desirable attributes mentioned above. This feature-set, if realized, can help in designing an ideal, low-cost sensing solution with integrated communications. The goal would be to leverage such solutions to achieve broader situational awareness and better management of assets in the distribution grid.
3.1 Introduction

The discussion so far highlights the shortcomings of typical ‘IoT-type’ sensor networks that have been proposed for monitoring and control applications in smart distribution systems. There is a strong need for decentralized monitoring and control operations for the future grid. The key enablers are intelligent solutions that offer higher level of automation with minimal customization without explicitly relying on bandwidth intensive communication channels to upload granular data to the cloud. The use of existing solutions have resulted in numerous challenges, as discussed so far. As a result, a new approach is required for achieving distributed, decentralized sensing, that satisfies the desirable attributes listed previously.

An interesting trend can be noticed over the past 10+ years— the smartphone has become a universally present, globally compatible resource for computing and communication. Most people\(^1\) own a smart phone [164] and carry it with them to all places they visit. Over the years, smartphones get upgraded through software updates which keep them up to date with changing technological standards while maintaining backward compatibility. Leveraging this trend, a novel communication and smart sensor architecture has been proposed for intelligently monitoring distribution system infrastructure while solving the aforementioned issues.

The GAMMA (Global Asset Monitoring, Management & Analytics) platform was developed at Center for Distributed Energy to solve the need for low-cost, scalable, global

\(^1\)Almost 3.2 Billion people in the world owned a smart phone in 2019
communications. GAMMA platform is an ecosystem of smart end nodes that can function autonomously (sense, compute, control) with minimal cloud input. It uses a novel communication architecture which resembles a delay tolerant network [171]. The platform is designed to solve the last mile connectivity problem, through special devices called ‘data mules’. Data mules are devices that physically relay the data packets between end devices and the cloud servers [172]. Data mules typically are special applications (apps) installed on smart phones, but they could also be physical devices like drones, mobile phones in service trucks, etc.

Any lineman, service truck, or customer who installs the GAMMA app automatically turns their devices into data mules for all devices in the GAMMA platform. The end nodes or sensors are equipped with a Bluetooth transceiver and can automatically connect to nearby data mules to send or receive data packets. The choice of Bluetooth makes the platform compatible with mobile phones, since Bluetooth (as opposed to other popular IoT short range radios like Zigbee, Z-Wave, custom RF etc.) is a globally compliant technology embedded in all smart phones. The data mule apps automatically forward the packets to the cloud server without being able to interpret or decrypt the data. The communication path is encrypted end-to-end using 128-bit Advanced Encryption Standard (AES–128), thus even if a data mule app gets compromised, no sensitive information can be exposed.

The whole platform is delay tolerant, and is most suitable for applications when on-demand connectivity is not required, and higher latency can be accepted. Due to data mules, and the use of a globally compliant standard, the need for additional country-specific certifications is minimized.

In addition to the ecosystem of smart edge devices, the cloud infrastructure is optimized for handling data from fleets of devices thus scaling and accommodating design needs. The cloud architecture supports the setting up of new applications without having to customize or redesign software/IT schemes, making it ideally suited for supporting millions of devices in the electric distribution system. Looking at the fleet level data, certain
value streams can be derived by using specialized algorithms that are important for system level optimization of the electrical network (e.g., data regarding power quality disturbances across the feeder can help understand & solve systemic issues). This chapter presents the details behind the platform design, its various elements and overall operations.

3.2 GAMMA Platform Overview

The overall platform architecture is shown in Fig. 3.1. The platform has three primary components— the edge devices or end nodes, the data mules, and the cloud. The edge devices are meant to be embedded into smart sensors or actuators, distributed in the field, capable of operating autonomously. They opportunistically communicate with the data mules and connect to the cloud through the data mules. The cloud is responsible for ingesting, storing and analyzing the data generated by the edge devices.

In this section, the assumptions, design constraints and operation of all components (end node, data mule and cloud server) of the communication platform have been briefly described.

The primary design criteria is the choice of communication protocol. This is an important consideration as it affects many factors like overall solution cost, power consumption, communication range, adoption rate and barriers to global deployment. Certain radio spectra are governed by International Telecommunication Union\textsuperscript{2} and need licensing before commercial use. Some radio protocols (e.g. cellular networks) need clearances and certifications before being deployed in different countries. In order to avoid the certification requirements, it is necessary to choose a standardized radio protocol like Zigbee, Bluetooth, Wi-Fi, LoRa, making global adoption seamless. A brief comparison of various popular short and long range radio protocols is summarized in Table 3.1.

\textsuperscript{2}International Telecommunication Union– ITU
Figure 3.1: Overview of GAMMA platform. The architecture offers an end-to-end solution with minimal customization.
Table 3.1: Comparison popular wireless protocols for smart grid sensor fusion

<table>
<thead>
<tr>
<th>Parameter</th>
<th>ZigBee</th>
<th>Bluetooth</th>
<th>Wi-Fi (WLAN IEEE 802.11.x)</th>
<th>LP-WAN</th>
<th>LoRaWAN</th>
<th>NB-IoT</th>
<th>Cellular (3G/4G/LTE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range</td>
<td>&lt; 1500 m</td>
<td>&lt; 1000 m</td>
<td>&lt; 1000 m</td>
<td>&lt; 10 km</td>
<td>5 – 20 km</td>
<td>1 – 10 km</td>
<td>&gt; 5 km</td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.15</td>
<td>0.3 – 0.15</td>
<td>~ 1 – 10</td>
<td>~ 0.05</td>
<td>&lt; 0.005</td>
<td>~ 0.2</td>
<td>&gt; 10</td>
</tr>
<tr>
<td>Power consumption</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>Moderate</td>
<td>High</td>
</tr>
<tr>
<td>Frequency (GHz)</td>
<td>2.4</td>
<td>2.4</td>
<td>0.9 or 2.4</td>
<td>&lt; 1</td>
<td>0.9</td>
<td>0.7 – 0.9</td>
<td>0.8 – 1.9 or 2.1</td>
</tr>
<tr>
<td>Network topology</td>
<td>Star, meshed</td>
<td>Star, meshed</td>
<td>Star</td>
<td>Star</td>
<td>Star, meshed</td>
<td>Star, meshed</td>
<td>Star</td>
</tr>
<tr>
<td>Support on Smartphone</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes, but not needed</td>
</tr>
<tr>
<td>Cost</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
<td>High, recurring</td>
</tr>
</tbody>
</table>
Looking at the most popular standards above, it can be noticed that only Bluetooth\(^3\) and Wi-Fi are protocols available in standard smart phones at no extra cost. This makes the use of Bluetooth an obvious choice for a distributed, low-cost, opportunistic platform that can leverage standard smart phones as data mules without additional hardware customization.

Although GAMMA is designed around Bluetooth Low Energy (BLE), without loss of generality, similar principles can be extended and applied to connections over Wi-Fi ad-hoc networks, since Wi-Fi (WLAN, IEEE 802.11) is also a globally standardized and available in all smart phones for no extra operational cost. However, the advantage of BLE is a lighter software stack (resulting in lower computation effort and power consumption on end device) and lower hardware costs. For example, compared to BLE, entry level Wi-Fi transceivers are twice as expensive (Wi-Fi chips cost $7, compared to $3 for BLE and RF front end [166, 167]), provide the same radio characteristics (BLE and Wi-Fi both would have $-96$ dBm receive sensitivity\(^4\), $+18$ dBm transmit power) and consume up to twice as much power\(^5\) in the active state (Wi-Fi 272 mA, BLE 160 mA when transmitting at $+20$ dBm), and up to 50 times as much power in the idle state (184 mA for Wi-Fi compared to 4 mA for BLE). Wi-Fi transceivers generally have a ‘network processor’ subsystem, capable of implementing Wi-Fi and internet protocols (like IEEE 802.11x, IPv4/v6 TCP/IP stacks, DNS, DHCP etc)[166], which results in significantly larger power consumption, software and code complexity, which may not be required for lightweight ‘edge-of-network’ applications. Similarly, if the application demands it, direct connectivity from the device to cloud can be achieved through cellular NIC (network interface cards), typically at higher costs.

\(^3\)BLE mesh is a relatively new architecture emerging

\(^4\)Receive sensitivity is the weakest signal that a transceiver can successfully receive
3.3 Functional Elements of GAMMA Platform

While building the GAMMA ecosystem, end nodes and data mules were designed with certain physical constraints in mind:

- The end node is a low-cost, energy constrained device (like a sensor or an actuator), without a dedicated internet access module (e.g., Ethernet/cellular NIC). It needs to communicate over BLE.

- Data mules refer to the smart phones equipped with popular mobile operating systems (e.g., Android and iOS) installed with the GAMMA data mule app. These phones support BLE specified in Bluetooth 4.0 or later.

- A data mule moves around a region which overlaps with one or more end node’s Bluetooth communication range, and has coverage of a (cellular or Wi-Fi) network to access the internet (and hence the app server). When internet connectivity is unavailable at the time the data mule connects to the end node, data can be temporarily stored on the data mule.

- Data mule has accurate positioning method (e.g., GPS), and its real-time location can be accessed by the app.

- The application server(s) can handle simultaneous communication with multiple data mules. The number of mules can expand rapidly and the server(s) can accommodate the scaling of system at a reasonable rate.

3.3.1 End Node Design

Since none of the end nodes have direct access to the internet, the network structure seen by the end node is a delay-tolerant network (DTN). The delay of a single trip between an end node and the server could range from a few seconds to several months depending on the availability of data mules. Thus, the end node stores the measurement data locally.
in an on-board flash memory, with a cyclic buffer to prevent overflow and minimize data loss. When first commissioned and when connecting to data mules the end nodes get UTC time (coordinated universal time for local real time clock updates), GPS coordinates and other configuration data from the commissioning packets it receives from the server (also relayed by data mules).

The end node acts as a peripheral BLE device and keeps advertising itself. As a data mule passes by and receives its advertisement, it establishes a connection with the end node. Because the end node does not have a pre-determined set of mule devices an end-to-end encrypted channel needs to be established between the end node and the cloud server. This is achieved by generating a randomized, unique key on each end node when it is configured in a secure environment (like a factory shop floor). This key is recorded at the server and is not accessible to the data mules, and hence the data mules can only relay the data between the cloud and the end nodes (bi-directional) without being able to tamper with an encrypted packet. The attack vectors and the network layer security scheme is shown in Fig. 3.2.

Another layer of security can be added by way of authenticating data mules by speci-
fying a pass-code when establishing the BLE connection, as noted in step 5 in the flowchart below. The full communication process is is visualized in Fig. 3.3.

A special type of end node, called the GAMMA Kernel+ (shown in Fig. 3.1 in red) is a combination of the Bluetooth-based GAMMA Kernel, and a cellular radio modem. This edge device can support all functionality of the GAMMA Kernel, while also offering an option for integrating cellular communication. The added functionality, while enabling real-
time communication, incurs additional complexity in terms of cost, power consumption (for instance, cellular modems cost upwards of $15 and need 1.5+ W of power, compared to GAMMA Kernel specifications which are summarized in Table 3.2) and the additional burden of regional cellular compatibility, certifications and fixed recurring costs.

3.3.2 Data Mules

Data mules bridge the gap between the data source (could be end node or server, depending on direction of data flow) and data sink. Data mules are devices with trusted partners (employees, linemen, contractors, etc.) that the electric utility can rely on to gather data from the field. The data flow between the source and the sink is enabled by the data mule’s ability to access both the BLE domain and the internet domain. Smart phones possess several advantages to serve as data mules—

- Phones cover a large area, since people carry them everywhere.

- A smart phone is equipped with more than one network access technologies, e.g., Wi-Fi, 3G/4G, Bluetooth. It can be a device that connects all these networks.

- Smart phones are equipped with various sensors (e.g. GPS), which allow the smart phone to collect locational information.

The data mule app can run in the background once correctly configured and when the user has been authenticated, so the user does not need to open it. Fig. 3.4 illustrates the flow chart for the app in terms of its communication pattern:

- Step 1: The app scans for location change of the data mule using GPS.

- Step 2: Once a change is detected, the app sends a query to the server with the data mule’s coordinates. If no change is detected, the data mule either finds nearby devices to connect (step 6), or loops back to step 1.
Figure 3.4: Flowchart of the logic running on data mule app.

- **Step 3, 4:** If the server is inaccessible, it retries during the next location update or when the internet connection has been restored. Otherwise, the server processes the query and searches for a set of end nodes near the data mule, then responds to the data mule with the Bluetooth MAC address, authentication information, and downlink data for each nearby end node.

- **Step 5:** The app then stores the results locally and scans for the advertisement from nearby BLE devices. It checks the Bluetooth MAC address in each advertisement found, and compares with the Bluetooth address received from the server.
• Step 6: If no match is found, the app repeats the above steps from the scanning until a timeout occurs. Once timed out, the app goes back to step 1.

• Step 7: Otherwise, the data mule app will establish a connection with the sensor node.

• Step 8: Once the Bluetooth link between end device and data mule is disrupted (e.g. when the data mule moves out of coverage area), the data mule app restarts from step 1 and continues onwards.

The app detects the location change of the data mule using GPS, and once a significant change is detected, the app sends a query to the server with the data mule’s coordinates. If the server is inaccessible, it retries during the next location update or when the internet connection has been restored. Otherwise, the server processes the query and searches for a set of end nodes near the data mule, then responds to the data mule with the Bluetooth MAC address, authentication information, and downlink data for each nearby end node. The app then stores the results locally and scans for the advertisement from nearby BLE devices. It checks the Bluetooth MAC address in each advertisement found, and compares with the Bluetooth address received from the server. If no match is found, it repeats the above steps from the scanning until a timeout occurs. Otherwise, the data mule will establish a connection with the sensor node. The next steps follow the corresponding part in the end node’s network timing diagram depicted in Fig. 3.3. After the data mule is disconnected with the end node, it keeps scanning for other end nodes nearby, until it moves away from the region and a new location change has been detected.

The Kernel+ can also be configured as a special type of device, called the hardware captive data mule, which essentially replaces the mobile phone and can offer a similar last-mile connectivity bridge (represented in Fig. 3.1). The devices in the field (GAMMA Kernels) can be continuously discovered by the GAMMA Kernel+ via Bluetooth. Necessary data are exchanged and the GAMMA Kernel+ pushes data to the GAMMA cloud.
using the cellular modem. This type of networking can communicate over longer distances as the pair of GAMMA Kernel and Kernel+ have a better radio link budget than a smart phone and GAMMA Kernel.

The choice of scanning (on data mules) and advertisement intervals (on end nodes) can favorably impact overall system throughput, however at the cost of higher energy consumption (on both the end node and the data mule). The optimal choice for these parameters is dependent on the application (e.g. [169] shows how to adaptively adjust scan intervals to minimize energy consumption).

3.3.3 Cloud Server

A fundamental goal of this application is to set up a communication channel between the server and each individual sensor node. Since there is no common physical media that can be used to establish a direct link between the two communicating parties, a data mule in the form of an app running on a smart phone is employed to set up a delay-tolerant network.

Despite the delay-tolerant nature of this network, the data mule is analogous to routers in a traditional computer network, and the server and end node are the two ends of an application layer communication channel.

One layer below the server-end node application layer is the direct link between the server and each data mule, whether through Wi-Fi, cellular or other means of internet access technologies. This part of the network is a classic heterogeneous network. A large number of mature protocols such as TCP and HTTP, can handle the communication with relative ease. GAMMA cloud\textsuperscript{6} is based on Google Cloud Platform [173] to manage collecting, processing, and storing data from data mules.

The server is responsible for end node management, data mule management, data cleansing, de-duplication and validating module and the actual data repository. The GAMMA Cloud Server is credited to Lalith Polepeddi, former member of GAMMA team.

\textsuperscript{6}The specific architecture and implementation of the GAMMA Cloud Server is credited to Lalith Polepeddi, former member of GAMMA team
analytics engine runs on the data stored in the final repository.

3.3.4 Network Setup

The communication network has a relatively simple topology compared to meshed sensor networks, due to its stratified structure. The server sits on the top layer and is the command center and ultimate sink of data. The middle layer is composed of large number of data mules moving in space. The bottom layer consists of the sensor nodes which collect data and actuate either locally or by responding to a command from the server. The direct communication only occurs between adjacent layers.

The network runs autonomously once it has been properly configured. On the server back end, a database needs to be set up, consisting of the expected locations, authentication credentials, and end-to-end encryption keys of all the sensors nodes that have been or will be deployed. A separate database for storing the actual data collected by each sensor node is also initialized. For a data mule, a user needs to register with the service in order to be part of the communication network. This requires identity verification, to track each data mule to a legitimate user. Once a user is registered and logged in, the credential for the users account is preserved and continues to authenticate the account.

The sensor node is usually not powered on until it has been installed on its target location. Once it is installed at a fixed point, it needs to be commissioned before it starts collecting data and joins the network. This can be achieved with a specially crafted version of the data mule app (operated by authorized users), which connects to the sensor node and performs the commissioning steps. The minimum required information that needs to be transferred into the sensor node includes:

- Current UTC time
- GPS coordinates, which can be obtained through the special data mule’s phone
- Parameters used for data measurement, related to the environment that the sensor is
Note, that the end-to-end encryption key can be either distributed to each sensor node during commissioning stage, or manufacturing stage in a factory.

### 3.4 GAMMA Kernel

Figure 3.5: GAMMA platform can enable an ecosystem of smart, autonomous devices that can perform control actions locally, while interacting with the cloud in a delay tolerant fashion. This is achieved by embedding the GAMMA Kernel in the end devices, making them compliant with GAMMA ecosystem.

GAMMA platform acts as a framework for smart, distributed, autonomous devices that can be deployed globally and can sense, compute, and take appropriate control action. A functional unit of the end (edge) node, called GAMMA Kernel has been designed and built, keeping in mind the basic requirements for the ecosystem to work. The block diagram of the GAMMA Kernel is shown in Fig. 3.6.

The GAMMA Kernel is designed around a BLE RF front end along with a Cortex M3 processor; memory to store data locally and a power management and storage unit that can accommodate a wide DC input range. Fig. 3.5 shows a typical framework where GAMMA Kernel can be used. With a target BOM cost of $< 4 in volume of 1 million, the GAMMA Kernel functions as the low-cost smart edge device, that combines local in-
intelligence, sensing and actuation capabilities to enable a decentralized smart grid, working with intermittent (delays up to several weeks) connectivity.

3.4.1 Attributes and Specifications

Table 3.2: GAMMA Kernel Specifications

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Form factor</td>
<td>7.5 cm × 4.5 cm</td>
</tr>
<tr>
<td>BOM Cost</td>
<td>$4 in volume of 1 million</td>
</tr>
<tr>
<td>DC power input</td>
<td>+3.5 V to +50 V</td>
</tr>
<tr>
<td>Average current consumption</td>
<td>6 mA @ +3.3 V</td>
</tr>
<tr>
<td>Supercapacitor runtime</td>
<td>20 min on full power</td>
</tr>
<tr>
<td>BLE EIRP</td>
<td>+20 dBm</td>
</tr>
<tr>
<td>BLE sensitivity</td>
<td>−101 dBm</td>
</tr>
<tr>
<td>Bluetooth range (LOS)</td>
<td>&gt;250 mtr</td>
</tr>
<tr>
<td>Data rate</td>
<td>1 Mbps</td>
</tr>
<tr>
<td>Analog inputs</td>
<td>0 to +3.3 V</td>
</tr>
<tr>
<td>Sampling Rate</td>
<td>&gt;3000 Hz</td>
</tr>
<tr>
<td>ADC specifications</td>
<td>12 bits, SAR ADC, 200 kS/sec</td>
</tr>
<tr>
<td>Memory</td>
<td>32 - 128 Mb, up to 1 year of data storage</td>
</tr>
</tbody>
</table>

The specifications of the GAMMA Kernel are summarized in Table 3.2\textsuperscript{7}. The Kernel

\textsuperscript{7}LOS stands for line of sight, i.e. an un-obstructed communication path
is designed to be a universal smart device that can be plugged into a user defined application (like AMI smart meter, smart inverters, volt-VAR control devices etc.) as desired. The Kernel offers a standardized form factor and interfaces that provide access to GPIOs, digital ports like SPI, I2C, UART and ADC capable pins.

The selected chipset, CC2640R2F was compared [167] to other BLE capable MCUs and System-on-Chips and bench-marked as a leader in all specifications. The SOC includes an ARM Cortex M3 processor clocked at 48 MHz, 275 kB of NV-memory, with 128 kB ISP-flash, 28 kB of SRAM, 8 kB cache that supports over-the-air updates. Advanced features include dedicated peripherals for UART, SPI, I²C, RTC and an AES–128 module for security. Besides, a streamlined design of a Real-time Operating System (RTOS) maximizes the multi-threaded task management between the Cortex M3, BLE engine and co-processor for edge-computing. The RTOS is organized into two periodic threads— one responsible for the Bluetooth communication interface and the other responsible for the sensor event management, data processing and housekeeping.

The GAMMA Kernel can function autonomously based on a local ‘rule-based’ engine. Using the parameters being sensed (e.g.− voltage, current, power, temperature), the GAMMA Kernel can autonomously compute control actions and actuate components to achieve necessary responses within millisecond intervals, as required by smart grid applications. Data mules can be used to slowly update the set-points on the end nodes, or even send commands for executing control sequences as desired.

GAMMA Kernel has advantages of minimal customization and software complexity, since sensing and control action thresholds can be remotely set from the cloud through data mules. This reduces significant software overhead and overall effort involved in deploying an application in the field. With integrated sensing and energy management, applications can be rapidly developed around a set of constraints, resulting in fast time to market. Since Bluetooth in smartphones is backward compatible, Bluetooth 4.2 (BLE) offers immunity to technology migrations. Upgrades to the data mule apps can be centrally handled. If needed,
firmware on end nodes can be updated through the data mule apps, using an over-the-air upgrade.

### 3.4.2 Memory Management

The GAMMA Kernel has an on-board 32 Mbit serial flash memory, interfaced through a 4 MHz SPI bus. The memory is divided into two sections— the data section, dedicated to granular, time series information; and the event section for storing operational anomalies recorded throughout. Each data point being recorded is time-stamped and has a generic, user-defined data structure that can be adapted towards the application in question. A cyclic buffer is maintained in both sections and the overall structure is first-in-last-out, prioritizing latest data first.

A typical data point is envisioned to be $\sim 20 - 40$ Bytes, ensuring that the memory is large enough to host approx. 6 months to a year at 15 min intervals.

![Figure 3.7: GAMMA Kernel memory interface.](image)

The cloud can command individual end-nodes to search and report data points or anomalies between arbitrary time stamps whenever connections are established.
3.4.3 Energy Management

The GAMMA Kernel is developed with a universal DC power interface that can operate over a wide range of $5 - 50 \text{ V}$, creating an internal $+3.3 \text{ V}$ voltage rail using a low drop out linear voltage regulator. This rail powers the full embedded system, including the MCU and the RF sub-systems.

For storing energy on the device, a $1 \text{ F}$ super-capacitor has been included on the $3.3 \text{ V}$ rail. This capacitor holds charge during events which cause the DC input voltage to drop out.

The GAMMA Kernel’s overall power consumption is minimal, and is mainly driven by the MCU and RF sub-systems. The digital sub-system consumes $6 \text{ mA}$ at $3.3 \text{ V}$, while the periodic BLE advertisements can result in a peak consumption of $25.5 \text{ mA}$. Each advertisement event lasts for $4 \text{ ms}$ and occurs (typically) every $100 \text{ ms}$. The energy characterization has been shown in Fig. 3.8.

![Figure 3.8: GAMMA Kernel Power characterization during communication events.](image)

Figure 3.8: GAMMA Kernel Power characterization during communication events.
3.5 Communication Interface and Connectivity Models

This type of networking falls under the traditional opportunistic networks and MANETs, which have been extensively studied [175], [180]. Consider \( \mathcal{N} \) end nodes distributed in a

Figure 3.9: Spatio-temporal representation of opportunistic connectivity.

Figure 3.10: Time varying graphs when connectivity exists between end nodes and data mule only during specific time windows.
given region, with $M$ data mules traveling in it. The data mules get specific inputs from
the GAMMA server in order to discover and pair with specific end nodes—typically those
which have not been synchronized in a long time, or if the cloud wants to downlink informa-
tion (like commands or rule updates) to particular nodes. This process is shown in Fig.
3.9. The resulting time varying connectivity graph is shown in Fig. 3.10. The time inter-
vals on each link indicate the period for which the individual links are active. The graph
$G = (V, E)$ has vertices $V =$ set of all end nodes, and edges $E =$ set of all links existing
temporally.

The following entities have been defined in the context of time varying graphs [175]:

$\rho : E \times T \rightarrow \{0, 1\}$ the ‘presence function’, indicating if the given link is valid or not.

In this opportunistic network, $\rho$ depends on:

(1) whether a data mule is in the vicinity (RF LOS range) of the end node.

(2) whether the end node advertises its presence to the data mule (through BLE advertise-
ment process).

(3) whether a data mule is ‘scanning’ for nearby end nodes.

Establishment of the link and consequently the presence function $\rho$ heavily depend on
the probability of end node being in advertisement mode (indicated by $P[advertisement]$)
and the probability of the data mule being in scanning mode ($P[scanning]$). We assume that
the data mules are always connected to the cloud (cellular or other means). Besides, if the
connection is disrupted, the data mules can locally store and cache data till the connection
is securely established again.

$\xi : E \times T \rightarrow T$ the ‘latency function’ indicating the time it takes for a packet to cross
the particular link. With BLE data rates (> 100 kbps), this term can be neglected.

We use a vertex centric evolution of the connectivity graph as shown in Fig. 3.11. The
parameters governing the connectivity (mainly $\rho$) are as follows:
Figure 3.11: ‘Vertex centric’ evolution of the time varying graphs with presence and latency functions. It is assumed that the data mules always have a stable cloud connection (through cellular or Wi-Fi access). However, if internet access is unavailable, data can be locally cached and transmitted later.

3.5.1 Process of Pairing

The presence function $\rho$ depends on the process of pairing between the end node and the data mule. These are governed by scanning and advertisement processes in BLE specifications [176]. The process of pairing is visualized in Fig. 3.12. Pairing can occur when the end node is ‘advertising’ over the BLE channels and the data mule passing-by, picks up these advertisements during its scanning phase.

Figure 3.12: Pairing process timeline. End nodes are BLE peripherals or ‘slaves’ while data mule applications on smart-phones act as BLE ‘masters’
Consider the data mule being in scanning phase for \( t_s \) duration and in the idle phase for \( T_s \) duration. Since it is a 2–state Markov chain, the probability of the data mule being in scanning phase at the \( n^{th} \) step when \( n \to \infty \) is \( \frac{t_s}{T_s} \). This can be verified as follows: Let \( \mathbb{P} \) be the transition matrix for the data mule:

\[
\mathbb{P} = \begin{bmatrix}
\alpha & \beta \\
\alpha & \beta
\end{bmatrix}
\]  

(3.1)

with \( \alpha = 1 - \frac{t_s}{T_s} \) and \( \beta = 1 - \alpha = \frac{t_s}{T_s} \). The eigen values are \( \lambda_1 = 0 \), \( \lambda_2 = (\alpha + \beta) \). Thus,

\[
\mathbb{P}^n = \mathbb{U} \begin{bmatrix}
0 & 0 \\
0 & (\alpha + \beta)^n
\end{bmatrix} \mathbb{U}^{-1}
\]

(3.2)

So \( p_{11}^{(n)} = A + B(1 - \alpha - \beta)^n \) for some \( A \) and \( B \). As \( p_{11}^{(0)} = 1 \) and \( p_{11}^{(1)} = 1 - \alpha \Rightarrow P_1 = p_{11}^{(n)} = \frac{\beta}{\alpha + \beta} = \beta = \frac{t_s}{T_s} \). Thus \( P[\text{scanning}] = \frac{t_s}{T_s} \). Similarly, it can be shown that, for the end node, \( P[\text{advertising}] = \frac{t_a}{T_a} \) where \( t_a \) is the duration the end node advertises, in a total cyclic period of \( T_a \).

Several studies [177] - [179] have shown the dependence of device discovery on BLE scanning, advertisement intervals and duty cycles. The optimal choice of scanning and advertisement intervals depend on parameters like energy consumption, intended advertisement miss rate, discovery latency among others. Relating network throughput with scanning and advertisement parameters is out of the scope for this work and will be addressed in the future. In the simulation setup, the overall process has a timeout implemented, with connections being considered valid only if they last longer than 5 sec (as an upper limit on the device discovery + connection phase), i.e. \( \rho(t) = 1 \iff (t_1 - t) > 5 \forall t_1 = \text{first connection instant} \). The process of evolution of \( \rho \) is visualized in Fig. 3.13.

A test to characterize how the connection times vary with advertising and scanning intervals was carried out. For a fixed advertisement interval chosen on the GAMMA Kernel, variation of the connection time was measured, due to the scanning process on the

82
Figure 3.13: Evolution of $\rho$ for a given pair of data mule and end node. Connectivity indicates whether a data mule is in the vicinity of an end node.

...data mule. The scanning interval $T_s$ was varied and the data mule was automatically connected to the Kernel through the scanning and node discovery process in the data mule. The variation of connection times was recorded through 20 consecutive experiments and have been captured in Fig. 3.14(a). Next, the advertisement interval $T_a$ on the GAMMA Kernel was varied for a fixed scanning interval $T_s$ and the connection times recorded through 20 consecutive runs as shown in Fig. 3.14(b).

From the above experiments, we can conclude that the overall connection process is dependent on $T_a$ and $T_s$ both.

3.5.2 Dependence on Radio Characteristics

The presence function $\rho$ depends on the BLE EIRP (effective isotropic radiated power) and RF sensitivity of the end nodes and the mobile phones. Since the system should be compatible with numerous phones from different manufacturers, the dependence is heavier on the RF parameters of end nodes. As seen in Table 3.2, the BLE EIRP of the nodes is $+20$ dBm, sensitivity is $-101$ dBm and the LOS distance over which a connection between
Figure 3.14: Variation of BLE connection times—(a) For fixed $T_a$ and varying $T_s$, (b) For fixed $T_s$ and varying $T_a$.

A smart phone and an end node can be sustained, is $>200$ m. These parameters effectively govern how long a connection can be maintained, once the pairing process is successful.

3.5.3 Data Mule Mobility Models

The presence function $\rho$ also depends on the mobility of data mules. These aspects and mobility models have been studied for VANETs and MANETs. In general, a stochastic motion was of interest and hence the Gauss-Markov mobility model was chosen [180], [181]. The motion of data mules was simulated in $x-y$ planar space as follows: Speed ($s_n$) and direction ($d_n$) are the two parameters of interest at the $n^{th}$ instant. They are varied as:

$$s_n = \alpha s_{n-1} + (1 - \alpha)s_{\text{mean}} + s_{\text{rand}}\sqrt{1 - \alpha^2} \quad (3.3)$$

$$d_n = \alpha d_{n-1} + (1 - \alpha)d_{\text{mean}} + d_{\text{rand}}\sqrt{1 - \alpha^2} \quad (3.4)$$

The speed statistics are adopted from [182] and plugged into the mean speed parameter above. Here, $s_{\text{rand}}$ and $d_{\text{rand}}$ are normally distributed speed and direction variables,
with \( s_{\text{rand}} \in [1, 5]\text{m/s} \) and \( d_{\text{rand}} \in [0, 360]^\circ \). In the \( x - y \) grid, the motion is governed by:

\[
x_n = x_{n-1} + s_{n-1} \sin(d_{n-1}) \tag{3.5}
\]

\[
y_n = y_{n-1} + s_{n-1} \cos(d_{n-1}) \tag{3.6}
\]

Compared to other models like random direction mobility and random waypoint, Gauss-Markov model has some advantages:

1. It tunes the randomness of the motion through a single parameter \( \alpha \), with \( 0 \leq \alpha \leq 1 \). By setting \( \alpha = 1 \), linear motion can be obtained, while \( \alpha = 0 \) yields totally randomized motion. For the mobility models of data mules, a value of \( \alpha = 0.8 \) is chosen to model real world motion.

2. It allows for past velocities and directions to influence the present values, an important factor affecting the trajectories of data mules. Since data mules are objects like smart phones, drones, utility trucks, the velocity cannot vary randomly. The velocity at the \( n^{th} \) instant governs the velocity at the \( n + 1^{th} \) instant in time.

3. The trajectories obtained are close to the ones one might expect in real-world scenarios [180].

An interesting aspect to note is that the actual connectivity and throughput of the network is insensitive to the speed of the data mule [179], but only depends on the time the data mule spends in the coverage of a particular end node.

### 3.5.4 Simulation Results

In order to study the interaction with mobile data mules, a simulation study was conducted using MATLAB. The link layer over BLE was emulated by constructing the connectivity graphs (as shown in Fig. 3.9 - 3.13) based on the trajectories of the data mules to
study variation of overall network parameters. A grid of 10 km by 10 km was constructed, with all data mules beginning their transit at random points within the grid. End nodes ($N = 100$ in number) were scattered randomly across the grid. Data mule transit for 10 hrs was simulated, with a 1s granularity.

Time step for the Gauss-Markov mobility model was 1s, however, a new speed value chosen from speed distribution statistics [182] every 600s. This ensures that enough granularity is obtained in the trajectories of data mules, while updating the velocities as per (3.3) and (3.4). The trajectory of data mules is governed by (3.5) and (3.6) noted above. A snapshot of the data mules’ mobility with respect to the locations of the end nodes is shown in Fig. 3.15.

![Figure 3.15: Sample trajectories of data mules around the $x − y$ grid. The red dots show locations of end nodes ($N = 100$) while the colored traces are the trajectories of data mules ($M = 25$).](image)

To study the overall performance of the opportunistic network, we look at total data exchanged between data mules and end nodes. Several parameters affect this throughput, namely: number of mules ($M$), connectivity range of end nodes, scanning duty cycles on data mules, advertising duty cycles on end nodes, and pairing time duration. Once the trajectory of data mules is obtained, the connection process is modeled as close to real life scenario as possible. Once an end node is in the vicinity of the data mule (governed by the RF LOS range), the connection process begins, and is modeled as a period of 5 sec when
no data transfer takes place. This is captured by the fact that $\rho(t) = 0$ for that period of initial connectivity (seen in Fig. 3.13). This process is carried out for all the $M$ data mules with respect to the $N$ end nodes.

Once a connection has been established, the data are exchanged as per over the air rates for BLE protocol. Even though BLE supports raw data rates upto 1 Mbps, the GAMMA protocol has some overhead in it, and this has been accounted in the study. An effective data rate\(^8\) of 1 kbps has been modeled. The variation of the data throughput with number of mules is shown in Fig. 3.16.

![Figure 3.16: Variation of overall data throughput with number of data mules $M$ and over time.](image)

\(^8\)This accounts for any restrictions different smart phone vendors impose on the overall throughput Bluetooth can achieve using that particular phone as a data mule
3.6 Experimental Feasibility of GAMMA Platform

In this section, a few experiments are documented to demonstrate the practical feasibility of GAMMA platform. The experimental scenarios showcase the platform’s capability to communicate different data formats, perform edge computational tasks, operate in arbitrary locations and test conditions.

3.6.1 Proof of Concept Application

For the purpose of testing and demonstrating the platform, five GAMMA enabled power quality sensors (shown in Fig. 3.17) were developed and deployed in various locations around Atlanta, USA. The sensors leveraged GAMMA Kernel’s capability to sample high speed data through the analog I/Os. The sensors record RMS voltage ($V_{rms}$) and frequency every 1 second. $V_{rms}$ is aggregated and an averaged data point is generated every minute, which is timestamped and stored in the local flash memory. The voltage waveform is sampled 64 times a cycle (i.e. $\sim 3.84$ kHz). Overall, 1% accuracy can be achieved and the system is configurable for both 120 V, 60 Hz or 240 V, 50 Hz systems.

Based on the value of $V_{rms}$, power quality events like voltage sags and swells, frequency deviation, outages are recorded. A surge detection circuit triggers every instant the voltage momentarily crosses a pre-determined threshold. The sensed waveforms are shown in Fig. 3.18.

Whenever a data mule is connected, averaged, 15 minute interval data (voltage and frequency) are reported to the cloud, along with the power quality events. The cloud server can issue commands to specifically request 1 minute resolution data from specific sensors between two given timestamps. Through GAMMA platform, the power quality sensors can achieve full duplex communication with the cloud.

GAMMA mule applications (shown in Fig. 3.17) installed on five phones, could connect to any of the sensor in its vicinity. The system was able to relay all device data
Figure 3.17: Device package developed and deployed to test GAMMA platform. Plug-in power quality meter records and stores grid voltage events (sags, swells etc) and communicates to the cloud via the data mule app. The app has a user interface to pull data from the cloud and display to the user.

to the cloud, and then extract data and actionable information from the server to display to the user. The sensors have been operational for 4 months and have uplinked a total 2 MB worth of data to the servers.

This sample application demonstrates the capability of the GAMMA Kernel itself to—

- Act as a flexible data acquisition unit.
- Locally store time-stamped, time series information.
- Opportunistically connect and uplink large series of information to the cloud through different data mules.
- Perform edge-computation on server requests for averaging time series data.
Figure 3.18: Voltage measurement and power quality event detection algorithm. Yellow trace is scaled voltage appearing on device ADC pin. Top traces (a) show AC voltage with a DC offset. Bottom traces (b) show AC voltage with an analog surge detecting circuit output.

3.6.2 Geo-location and Asset Tracking

Figure 3.19: Map shows GPS tags of datamules when the connections were established with GAMMA devices. On April 4th, device #5, connected at two different geographical locations. Analytics can detect & alert the fleet manager that the asset has been moved twice between April 4th & April 5th.
The platform provides additional functionalities like asset tracking through GPS. Data mules separately append the GPS tag to each uplinked packet. Thus, the platform can inherently provide locational data to the server and can recognize if an asset has been moved. As an example, device #5 was moved from Georgia Tech campus to a location off campus. The platform can infer this location change, from the connection information reported by the mules as seen in Fig. 3.19 and can alert the fleet manager if necessary.

### 3.6.3 Interfacing Specialized Peripherals and Global Operability

The GAMMA Kernel can be interfaced with external, specialized transducers and peripherals for performing more complex tasks. One such example is an energy metering unit with breaker functionality.

![GAMMA based AMI unit](image)

**Figure 3.20:** GAMMA based AMI unit, capable of smart metering, remote disconnect, VAR compensation. Prototype unit operated in Accra, Ghana (recorded location shown on top left). Two remote disconnect commands issued from Atlanta, USA to the device in Ghana.
GAMMA platform can be used to build low-cost AMI networks, by leveraging intermittent connectivity and intelligent smart meters. The smart meters can operate autonomously, performing sensing, local computation and take necessary control action depending on sensed parameters. The smart meters capable of bidirectional (net) metering, PAYGO electric billing, smart disconnect (based on account delinquency, fault detection or server-initiated turn off), volt-V AR optimization at the grid edge (based on programmable thresholds that can be changed from the cloud). The device can also implement dynamic pricing.

In order to test the control capability of GAMMA platform, the prototype was tested in Ghana, Africa\(^9\). The prototype and the test results are depicted in Fig. 3.20. More details on this application can be found in Appendix A.

### 3.6.4 Field Test Results for Opportunistic Communication

In order to show the viability of the platform, preliminary results from field tests performed with GAMMA Kernel are presented. With an enhanced BLE EIRP of \(+20\) dBm and a sensitivity down to \(-101\) dBm, a LOS range of more than 250 meters is expected in urban settings. The tests were performed with a generic smart phone and the GAMMA Kernel in urban, semi-urban and rural settings\(^10\) (Fig. 3.21). Demonstrations (summarized in Table 3.3) show BLE connections being established at distances over 200 m and sustained for more than 400 m.

GAMMA Kernel operation in a ‘drive-by’ mode was also verified. The Kernel advertises over the BLE advertisement channels every 10 ms, while the data mule tries to connect and receive data from the Kernel in the background.

Fig. 3.22 shows comparison in a semi-urban and an urban scenario. Fig. 3.23 shows tests performed in a semi-urban scenario at varying speeds. Connections could be estab-

---

\(^9\)Many thanks to Frank Lambert of CDE who took the prototype to Ghana during his conference visit

\(^{10}\)The urban and semi-urban locations were on Georgia Tech campus, while the rural setting was at Piedmont park meadow in Atlanta
Figure 3.21: Field tests performed in 3 locations (semi-urban, urban and rural) to find maximum distance at which a new BLE connection can be established (shown as D1, yellow trace being LOS) and maximum distance over which the connection can be sustained (shown as D2, red trace being LOS), between the GAMMA Kernel (denoted by ‘K’) & data mule app running on a generic mobile phone (denoted by ‘P’).

Established at distances over 100 m in a moving vehicle, and could be sustained up to 244 m while driving at different speeds and in the presence of obstructions. This test was also used to characterize the total time that the connection can be sustained and the amount of data that can be exchanged in the connection interval. The test summary is shown in Table 3.4.

Table 3.3: Results from a stationary LOS field test

<table>
<thead>
<tr>
<th>Location</th>
<th>Distance to connection ‘D1’ (m)</th>
<th>Distance to disconnection ‘D2’ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi-urban</td>
<td>201</td>
<td>463</td>
</tr>
<tr>
<td>Urban</td>
<td>174</td>
<td>257</td>
</tr>
<tr>
<td>Rural</td>
<td>202</td>
<td>283</td>
</tr>
</tbody>
</table>
Figure 3.22: Drive-by scenario: Mobile phone (denoted by ‘P’) placed in generic car & driven around in urban (location 1) and semi-urban (location 2) locations. Map shows locations at which new BLE connection was established (shown in blue) and maximum LOS distance over which the connection could be sustained (red trace).

Figure 3.23: Drive-by scenario: Mobile phone (denoted by ‘P’) placed in generic car & driven around in semi-urban location. Tests at 30 km/hr (top) and 50 km/hr (bottom) show locations at which new BLE connection can be established (shown as D1, yellow trace) and maximum distance over which the connection can be sustained (shown as D2, red trace).

Table 3.4: Results from a field test of ‘Drive-by’ scenario

<table>
<thead>
<tr>
<th>Speed (km/hr)</th>
<th>Time (sec)</th>
<th>Data (Bytes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>83</td>
<td>6464</td>
</tr>
<tr>
<td>50</td>
<td>61</td>
<td>1920</td>
</tr>
</tbody>
</table>
A similar test was performed on a bicycle: Data mule traveling at various speeds on a bicycle tried to establish BLE connection with the GAMMA Kernel. Table 3.5 summarizes the results of the tests. As expected, as the speed of the data mule increases, the time for which the connection is sustained decreases and amount of data that can be exchanged also reduces.

Depending on the application and context, distribution network assets can be either densely located (several devices in a few hundred meters) or sparsely dispersed (few devices in several kilometers). In order to maximize coverage, it is desirable that the data mule can sustain simultaneous active connections with multiple GAMMA Kernels. This specification is governed by the mobile phone’s hardware and native operating system (e.g. Android M supports 7 simultaneous BLE connections [174]). A simple test to verify 10 simultaneous connections was performed. A data mule could discover and connect to all 10 GAMMA Kernels in its vicinity and exchange data with them, uplinking 112 bytes from each device per minute (typical data packet size and generation interval).

Table 3.5: Results from a field test of ‘Bike-by’ scenario

<table>
<thead>
<tr>
<th>Speed (km/hr)</th>
<th>Time (sec)</th>
<th>Data (Bytes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>101</td>
<td>8800</td>
</tr>
<tr>
<td>10</td>
<td>85</td>
<td>5456</td>
</tr>
<tr>
<td>15</td>
<td>107</td>
<td>8016</td>
</tr>
<tr>
<td>20</td>
<td>61</td>
<td>3440</td>
</tr>
<tr>
<td>25</td>
<td>49</td>
<td>2032</td>
</tr>
</tbody>
</table>

Showing the feasibility of such a ‘data mule’ based platform is similar to analyzing throughputs of vehicular ad-hoc networks (VANETs), which have been extensively studied in literature [182]. The system throughput of GAMMA depends on the number of data mules registered in the network. However, for electric utilities, with trusted agents acting as data mules, a small number of data mules can cover a large fleet of devices (end nodes) installed in a distribution network. This scheme is similar to AMR infrastructure that has been proposed in [40]. However, with no custom hardware requirements, agents can drive
around, and connect to distributed assets. With specific guidance on nodes that have not been covered, a small group of agents can effectively cover a large number of distributed end nodes in the field.

### 3.7 Concept of Distributed Intelligence at the Edge

Based on the above discussion and experiments, following observations can be made from the data—

- GAMMA Kernel can act as a data acquisition unit or interface with more complex peripherals to function as an application specific sensor or control card.

- GAMMA Kernel can record and locally store data at various time horizons, including fast, sub-cycle events as well as slow, long-time horizon events. The data is time-stamped and recorded in the device memory.

- Due to the unique architecture, a bulk of the data can reside at the edge of the network and only alerts or critical information that is relevant for utility grid monitoring purposes can be uplinked to the cloud.

- The data that are communicated to the cloud through different data mules can either be alerts pertaining to situational awareness or standard time-series data.

- Depending on the application, the data can be extracted and analyzed either locally (on the GAMMA Kernel), or in the GAMMA Cloud Platform. Thus GAMMA Kernel can function as an edge-computing node within an opportunistic networking regime.

- The opportunistic networking works in different environments like urban, semi-urban and rural locations and different mobility models (like a moving car or a person riding a bicycle). It can also function across geographical borders without certification and special provisions.
Thus, GAMMA Platform offers a unique communication architecture that is well suited for applications where data delivery to the cloud is not very time-sensitive. It offers the unique ability to configure end nodes (GAMMA Kernels) to act autonomously as per different unique applications. The end nodes can acquire data, store it locally, and analyze it as per each application’s requirement. The extracted alerts are uplinked to the cloud through data mules as shown in Fig. 3.24.

This creates a framework for ‘distributed intelligence at the edge of the network’ where each sensor or control device has the ability (through GAMMA) to function autonomously without constant cloud inputs or communication and offer a fast control response to local events.

Figure 3.24: Proposed approach with GAMMA Platform and data mules can process most of the data on the sensor and upload alerts and summaries of recorded anomalies for the smart distribution grid.
3.8 Comparison of GAMMA Platform with State-of-the-Art IoT Architectures

A head to head comparison of GAMMA platform with other proposed platforms [19] - [40] is presented in Table 3.6.

<table>
<thead>
<tr>
<th>Feature</th>
<th>State of the art</th>
<th>GAMMA Platform</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Communications</strong></td>
<td>Cellular, Custom RF, Zigbee, Wi-Fi, LoRaWAN, 6LoWPAN, PLC</td>
<td>BLE 4.2/Wi-Fi with mobile phones</td>
</tr>
<tr>
<td><strong>Device cost for connectivity</strong></td>
<td>$40 to $200</td>
<td>$4</td>
</tr>
<tr>
<td><strong>Technology migration</strong></td>
<td>Cellular based systems not immune, other RF based may be immune</td>
<td>Immune</td>
</tr>
<tr>
<td><strong>IT &amp; integration costs</strong></td>
<td>High</td>
<td>Minimal</td>
</tr>
<tr>
<td><strong>Maintenance of wireless AP</strong></td>
<td>Required, expensive</td>
<td>Not required, uses datamules actual costs</td>
</tr>
<tr>
<td><strong>Backhaul infrastructure &amp; costs</strong></td>
<td>Required, can be expensive depending on application</td>
<td>Not required, uses datamules</td>
</tr>
<tr>
<td><strong>Energy consumption</strong></td>
<td>Depends on technology</td>
<td>Low</td>
</tr>
<tr>
<td><strong>Computational needs</strong></td>
<td>Generally higher (cellular, RF mesh, Wi-Fi/IoT like systems)</td>
<td>Low</td>
</tr>
<tr>
<td><strong>Data &amp; power management</strong></td>
<td>Add more costs to the system</td>
<td>Built-in</td>
</tr>
<tr>
<td><strong>GPS information</strong></td>
<td>Not present inherently, available at higher costs</td>
<td>Inherently available through datamules</td>
</tr>
<tr>
<td><strong>Certifications</strong></td>
<td>Required depending on technology</td>
<td>Minimal, globally certified</td>
</tr>
<tr>
<td><strong>Cybersecurity</strong></td>
<td>Not secure</td>
<td>Inherently secure</td>
</tr>
</tbody>
</table>

The table shows the several advantages GAMMA platform has over other solutions making it more suitable for deploying distributed, low-cost sensing and monitoring solutions for the power grid. The next few chapters explore the design of low-cost, intelligent sensors for the distribution network.
CHAPTER 4
LOW-COST, “CLIP-ON” CURRENT SENSOR WITH WIDE DYNAMIC RANGE

4.1 Introduction

The GAMMA platform enables various ‘edge-intelligent’ sensor and actuation devices to be developed using a standard ad-hoc networking architecture using data mules. The ability to develop, deploy and operate numerous sensors for the distribution network at a low-cost is crucial for achieving greater visibility, insights and control in the operational aspects of the distribution grid. Particularly, with edge-intelligence, the sensors are able to capture anomalies and perform analytical operations in-situ, converting them into edge-computing nodes in the smart grid.

As discussed earlier, current sensing is one of the most challenging issues in the distribution network. Present sensors particularly involve a high level of customization, lack the ability to be installed quickly in the field and cannot be used across a wide operating range—steady state as well as the rare fault mode.

In this chapter, we examine a method to design ‘clip-on’ current sensors based on the Rogowski coil principle. As discussed previously, Rogowski coil sensors are attractive on multiple fronts. Rogowski coils work on Faraday’s law of electromagnetic induction, but as opposed to CTs, Rogowskii coils do not use magnetic elements. The cores are made from non-ferrous material (typically air or plastic cores) and thus, they do not saturate. This allows Rogowski coils to inherently achieve a high dynamic range, with a linear response without the limitation of saturation or distortion at high primary currents. The coils are immune to external noise and offer electrical isolation, which is required for power line applications. Further, since Rogowski coils are $di/dt$ sensors, the signal can be reconstructed through an integrator stage, as part of the signal conditioning circuitry. This allows
Rogowski coil sensors to operate with a high bandwidth.

Figure 4.1: Various components involved in a Rogowski coil based power line current sensor [90]. An integrator is required to get a signal proportional to the primary current $i_p(t)$ from the induced voltage $v_o(t)$.

With rapid advances in PCB-fabrication techniques, it has been possible to embed complex copper traces into PCBs at low cost. This method is highly scalable (as PCB costs drop with high volumes) and manufacturers guarantee repeatability of parameters—i.e. identical PCB designs have the same physical parameters. While significant work exists in developing PCB-embedded Rogowski coils (summarized in Table 2.3), they cannot be retro-fit around existing conductors in the field as they need to encircle the conductors. This chapter explores the possibility of a split-core PCB-embedded Rogowski coil, ensuring a retro-fit capability. Additionally, this chapter presents the design for an intelligent, adaptive, “auto-tuning” signal conditioning stage. This enables the sensor to be used across a wide operating range, including for capturing unexpected fault modes.

4.2 Rogowski Coil Modeling and Operating Principles

For constructing Rogowski coils using a wire-wound structure, a non-ferrous core is chosen, around which the wire is wound in a toroidal manner, so as to create a closed loop. Typically, the core can be made from flexible material, which can be ‘wrapped’ around any
conductor of interest, resulting in a sensor that can be quickly installed around a conductor. With PCB-based Rogowski coils, however, the material (substrate) is inflexible. For a quick and easy installation, the PCB could be ‘split’ into two halves which can be ‘clipped’ around the conductor in the field.

Consider current $i_p(t)$ flowing through a conductor that is encircled by the coil. By Ampere’s law, the magnetic field and current along the axis of the torus are related as—

$$i_p(t) = \oint H(t) \cdot ds = \oint \frac{1}{\mu_0} B(t) \cdot ds$$  \hspace{1cm} (4.1)

where $s$ is the distance along the closed loop.

In order to obtain the voltage $v(t)$ induced at the PCB-embedded coil’s terminals, an analytical method can be used as follows—

![Geometry of a PCB embedded Rogowski coil.](image)

Consider the top view and the side view of the PCB-embedded Rogowski coil as shown in Fig. 4.2. If $h$ is the thickness of the PCB, and $a$, $b$ are the inner and outer diameters of the PCB coil, the goal is to relate mutual inductance $M$ to the primary current $i_p(t)$ and the geometry of the coil, namely $a$, $b$ and $h$.

The magnetic field strength $H$, magnetic flux density $B$, at a point which is at a
distance \( x \) away from the conductor carrying current \( i_p(t) \) is—

\[
H = \frac{i_p}{2\pi x} \Rightarrow B = \mu_0 \cdot \frac{i_p}{2\pi x}
\]  

(4.2)

where \( \mu_0 \) is the permeability of free space, \( 4\pi \times 10^{-7} \text{H/m} \)

We can find the flux linked in an area of cross section \( dA \) by integrating the magnetic flux density as—

\[
\phi = \int_{a/2}^{b/2} B \cdot dA
\]  

(4.3)

The unit area \( dA \) is actually an infinitesimally small cross-section of the PCB coil. Thus, \( dA = h \cdot dx \). So we can evaluate \( \phi \) as—

\[
\phi = \int_{a/2}^{b/2} \mu_0 \cdot \frac{i_p}{2\pi x} \cdot h \cdot dx = \frac{i_p \mu_0 h}{2\pi} \cdot \ln\left(\frac{b}{a}\right)
\]  

(4.4)

For a coil with \( N \) number of turns on the PCB; by Faraday’s law, voltage induced on the coil, \( v_o \) is—

\[
v_o = -N \cdot \frac{d\phi}{dt} = -N \cdot \frac{\mu_0 h}{2\pi} \cdot \ln\left(\frac{b}{a}\right) \cdot \frac{di_p}{dt}
\]  

(4.5)

Thus, we can get a closed form expression for the mutual inductance \( M \), which can be represented by—

\[
M = -N \cdot \frac{\mu_0 h}{2\pi} \cdot \ln\left(\frac{b}{a}\right)
\]  

(4.6)

Note that the negative sign in equation (4.6) is derived from Lenz’s law.

Typically, for power line applications, current \( i_p(t) \) is actually a sinusoid of angular frequency \( \omega \).

\[
i_p(t) = i_o e^{j\omega t} \Rightarrow v_o(t) = -Nj\omega \frac{\mu_0 h}{2\pi} \ln\left(\frac{b}{a}\right)i_o e^{j\omega t}
\]  

(4.7)

The expression (4.7) provides a direct relation between the voltage \( v_o(t) \) induced
across the terminals of the Rogowski coil with respect to the current $i_p(t)$ flowing in the enclosed conductor. It can be seen that the voltage varies directly with the frequency of the primary current, making the Rogowski coil suitable for *high frequency* current measurements, as $v_o(t)$ is proportional to $\omega$. It can also be observed that $v_o(t)$ is directly proportional to $di_p/dt$, making the Rogowski coil a $di/dt$ sensor.

### 4.3 Lumped Parameter Model of PCB-based Rogowski Coil

Each Rogowski coil can be expressed as an equivalent model of series $L, C$ and $R$ lumped parameters [84, 88]. These parameters determine the frequency characteristics of the coil, and namely the bandwidth over which the coil can be used as a ‘differentiating’ transducer. This represents the useful region of operation for the Rogowski coil. In this section, we examine the lumped parameter model and actual measurements with the aim of validating the Rogowski coil’s self-resonant frequency.

The equivalent circuit of a Rogowski coil is shown in Fig. 4.3.

![Figure 4.3: Lumped parameter model of a PCB embedded Rogowski coil.](image)

The self-inductance $L_s$ and series resistance $R_s$ can be derived as follows:

Consider the coil\(^1\) with $N$ turns, carrying a current $i'(t)$. From (4.2), the relation

\(^1\text{Note that for self-inductance calculation, we consider the coil is carrying the current, rather than the primary conductor.}\)
between $B$ and $H$ for a toroid of radius $r$ with $N$ turns can be written as—

$$B = \mu_0 \frac{N i'}{2\pi r}$$  \hspace{1cm} (4.8)

Thus, the inductance $dL_s$ can be found as—

$$dL_s = N \frac{d\phi}{i'} = N \cdot \frac{B \cdot dA}{i'} = N \cdot \frac{N\mu_0 h}{2\pi r} \cdot dr$$  \hspace{1cm} (4.9)

From this, $L_s$ can be obtained as—

$$L_s = N^2 \mu_0 h \cdot \int_{a/2}^{b/2} \frac{dr}{r}$$  \hspace{1cm} (4.10)

Thus, we get—

$$L_s = \frac{N^2 \mu_0 h}{2\pi} \ln\left(\frac{b}{a}\right)$$  \hspace{1cm} (4.11)

For calculating the series resistance $R_s$, we estimate the length of the coil and use standard expression for resistance of a wire $R = \rho \cdot l/A_w$, where $\rho$ is the electrical resistivity of PCB traces (for copper, $\rho = 1.68 \times 10^{-8} \ \Omega \cdot m$), $l$ is the length of the wire, $l = 2N \cdot d_l$, where $d_l$ is length of trace on top layer of PCB. $A_w$ is the cross sectional area of the PCB wire trace. Assuming the PCB trace is rectangular in cross section with cross sectional height $d_h$ and width $d_w$, $A_w = d_h \cdot d_w$, thus—

$$R_s = 2N \rho \frac{d_l}{d_h \cdot d_w}$$  \hspace{1cm} (4.12)

The lumped capacitance $C_s$ for a PCB embedded coil needs finite element methods to derive a closed-form expression [84]. In lieu of this, an experimental approach has been adopted.

Four Rogowski coils (designated as coils $A, B, C, D$) with slight variation in the physical characteristics were fabricated, with the aim of studying variation within $L_s, C_s, R_s$ and
The variation would help in determining if a split-core structure is viable or not. The four coils are pictured in Fig. 4.4.

![Figure 4.4: Comparison of the four PCB-based Rogowski coils fabricated. Coils C and D can be clipped onto conductors.](image)

Coil A is a solid-core PCB coil, with 64 turns and with a PCB thickness of 1.575 mm, coil inner diameter of \( a = 25 \text{ mm} \) and outer diameter of \( b = 55 \text{ mm} \). Coil B also has a solid core, with the same number of turns and physical dimensions \( a, b \), except the PCB thickness, which has been increased to 3.988 mm. Coils C and D have a split-structure joined together with connectors as shown in Fig. 4.4. They have the same physical parameters \( a = 22 \text{ mm} \) and \( b = 41 \text{ mm} \), but have different number of turns and connectors across the PCBs.

For the coils described above, experimental measurements for impedance \(|Z|, L_s, C_s, R_s\) and \(f_r\) were recorded using an Agilent™ E4990A Impedance Analyzer, shown in Fig. 4.5.

A summary of the measured parameters as compared to the expected values is shown in Table 4.1.
Figure 4.5: Impedance trends of the unloaded coils tested on Agilent™ E4990A Impedance Analyzer. No resonance observed till $f = 10$ MHz, indicating $f_r > 10$ MHz.
Table 4.1: Comparison of expected and measured parameters of the printed coil at $f = 60$ Hz

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coil A</th>
<th></th>
<th>Coil B</th>
<th></th>
<th>Coil C</th>
<th></th>
<th>Coil D</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expected</td>
<td>Measured</td>
<td>Expected</td>
<td>Measured</td>
<td>Expected</td>
<td>Measured</td>
<td>Expected</td>
<td>Measured</td>
</tr>
<tr>
<td>$L_s$</td>
<td>3.552 $\mu$H</td>
<td>3.375 $\mu$H</td>
<td>5.645 $\mu$H</td>
<td>5.986 $\mu$H</td>
<td>2.255 $\mu$H</td>
<td>2.238 $\mu$H</td>
<td>2.96 $\mu$H</td>
<td>3.103 $\mu$H</td>
</tr>
<tr>
<td>$R_s$</td>
<td>5.95 $\Omega$</td>
<td>5.59 $\Omega$</td>
<td>7.798 $\Omega$</td>
<td>7.738 $\Omega$</td>
<td>7.358 $\Omega$</td>
<td>7.045 $\Omega$</td>
<td>10.72 $\Omega$</td>
<td>11.392 $\Omega$</td>
</tr>
<tr>
<td>$C_s$</td>
<td>N/A</td>
<td>7.4 pF</td>
<td>N/A</td>
<td>15.2 pF</td>
<td>N/A</td>
<td>5.799 pF</td>
<td>N/A</td>
<td>5.281 pF</td>
</tr>
<tr>
<td>$M$</td>
<td>16.2 nH</td>
<td>17 nH</td>
<td>41.27 nH</td>
<td>44.78 nH</td>
<td>15.68 nH</td>
<td>15.5 nH</td>
<td>19.61 nH</td>
<td>19.91 nH</td>
</tr>
<tr>
<td>$f_r$</td>
<td>39.3 MHz</td>
<td>&gt; 10 MHz</td>
<td>21.18 MHz</td>
<td>&gt; 10 MHz</td>
<td>44.18 MHz</td>
<td>&gt; 10 MHz</td>
<td>39.31 MHz</td>
<td>&gt; 10 MHz</td>
</tr>
</tbody>
</table>
To compare the performance of the four coils head-on, they were excited with the same current $i_p = 1.2 \text{ A}_{\text{rms}}$ at 60 kHz with the aim of comparing the voltage output ($v_o = Mdi/dt$). The test results are shown in Fig. 4.6. From this, we see that the response of the four coils is comparable, with the closed-core coils $A$ and $B$ performing slightly better than coils $C$ and $D$. The only dominant factor is mutual inductance $M$. This proves that the clip-on coils are a viable option as a current transducer.

![Figure 4.6: Comparison of the coil outputs when excited by primary current $i_p = 1.2 \text{ A}_{\text{rms}}$ at 60 kHz.](image)

To ensure that the coil performs well with fast current transients, the voltage output was measured when the input current was given a step. The aim of this experiment was to make sure that the output voltage settles quickly, ensuring that the capacitive elements in the lumped parameter model do not contribute adversely to the overall performance. The step response for coil D is shown in Fig. 4.7, showing a fast settling $di_p/dt$ output for an excitation current of $i_p = 333 \text{ mA}_{\text{pk–pk}}$. 

108
Figure 4.7: (Green trace) Step response of coil D for a (pink trace) 100 kHz, 333 mA_{pk−pk} square wave primary current, \( i_p \). Zoomed in version shows fast settling time (< 200 ns).

4.4 Variation of Mutual Inductance with Conductor Location

An intuitive problem to be studied when developing a split-PCB Rogowski coil would be the variation of mutual inductance \( M \) with respect to the location of the conductor inside the coil structure. With a split-PCB structure, the coil becomes discontinuous around the edges, where the board-to-board connectors are located. The lack of tightly coupled turns around the edge could cause the mutual inductance to vary if a conductor is located near the edge of the coil, thus defeating the purpose of the clip-on design. An experiment to quantify the variation of mutual inductance \( M \) was performed as follows—

An acrylic (non-magnetic) disc with holes punched out for different possible conductor locations was fabricated as shown in Fig. 4.8. The conductor was excited with a source to generate a primary current of interest and the Rogowski coil output voltage was mea-
The mutual inductance $M$ was calculated using (4.6) and (4.7). It was observed that the normalized mutual inductance $M$ varied within $\pm 3\%$ as the position of the conductor was changed as shown in Fig. 4.8.

![Diagram showing variation of mutual inductance with conductor position](image)

Figure 4.8: Variation of the mutual inductance $M$ with conductor position inside the Rogowski coils (coils C and D). Up to $\pm 3\%$ variation is observed.

The above observation is in agreement with prior work found in literature, pertaining to wire-wound Rogowski coils [111]. For a Rogowski coil with an air gap without any compensation, the mutual inductance $M$ varies as little as $3.52\%$ when the conductor is near the airgap. It also has little variation in other arbitrary locations inside the coil which is confirmed from our findings.

It is important to note that the sensor is designed for utility grade cables typically found in the power grid (e.g. ACSR or $1/0 - 4/0$ gauge cables). As these cables would occupy the bulk of the Rogowski coil internal space, the expected positional variance is minimal.

Following observations can be made from the experimental data so far—
• The design methodology and operating principles of a PCB-based Rogowski coil has been successfully verified.

• A detailed $LCR$ model can be developed through a combination of analytical and experimental methods. The coils developed so far can work up to frequencies of 10 MHz.

• The capacitive elements do not deteriorate the high-speed response of the Rogowski coil.

• The mutual inductance $M$ is the main differentiating element with respect to the performance of the four coils. It mainly only depends on the physical dimensions of the coil, and not on the fact that a coil has a closed-core or a split-core structure.

• For a coil with a split-PCB structure, the positional variation of mutual inductance is within specifications compared to regular, wire-wound Rogowski coils.

Above experimental results show that an open-core, clip-on configuration (used in coils $C$ and $D$) has a performance comparable to that of the closed core designs (used in coils $A$ and $B$). We also see that the connectors do not introduce significant noise or parasitics into the lumped model of the Rogowski coil, as concluded from Table 4.1. We also see that the dynamic performance is within specifications, making the clip-on configuration ideal for a wide bandwidth application. This is the key enabler for a low-cost sensing solution for utility applications, that can be retrofitted around any existing conductor in the field.
4.5 Analog Design of the Signal Conditioning Stage

The next aspect of the Rogowski-based current sensor design is the analog signal conditioning stage. However, before designing the integrator and related circuits for the sensor, it is necessary to understand the frequency domain behavior of the overall sensor.

4.5.1 Frequency Domain Behaviour of the Rogowski Coil Sensor

As we have established, the Rogowski coil is a \( \frac{di}{dt} \) sensor—i.e. a differentiating element to a system input of current. In the frequency domain, the corresponding response appears like that of a first order differentiator, i.e. a gain response of +20 dB/decade as shown by the red trace in Fig. 4.9.

![Frequency domain design of Rogowski coil sensor](image)

Figure 4.9: Frequency domain design of Rogowski coil sensor: Red trace shows the frequency response of the Rogowski coil, green trace shows analog integrator response and blue trace shows the combined response of the coil and integrator.

The coil behaves as a differentiating element as long as it is operating below the coil self-resonant frequency \( (f_r) \). Beyond \( f_r \), the gain of the Rogowski coil starts rolling off at \(-20 \) dB/decade and for designs with an active integration stage, this is an undesirable operating zone.

The frequency response of an op-amp based analog integrator is shown in Fig. 4.9.
in green. The $-20$ dB/decade roll off is the region where the integrator can produce a meaningful output. Thus useful integration zone is the portion of the negative roll off that has a positive ($> 0$ dB) gain. Consequently, the DC gain basically sets the integration bandwidth since the roll off for the first order integrator is constant at $-20$ dB/decade.

When the Rogowski coil and the integrator stage are combined, the frequency response show in blue is obtained (Fig. 4.9). The desirable operating range with the complete sensor is the part of the frequency range where the Rogowski coil’s $+20$ dB/dec and the integrator’s $-20$ dB/dec cancel out to produce a flat ($0$ dB/dec) gain trend.

A few observations can be made from this—

- The Rogowski coil’s gain response improves as the frequency of the current increases. At lower frequencies, the Rogowski coil gain response is often less than $0$ dB. In other words, many Rogowski coils will produce a very small voltage signal at $60$ Hz frequencies.

- The overall design is dictated by the DC gain of the integrator, $0$ dB cross-over point for the integrator and the self-resonant frequency of the Rogowski coil.

4.5.2 Analog Design

Thus, as long as the Rogowski coil is operated below the self-resonant frequency $f_r$, the coil behaves like a differentiating element, ensuring that it can generate a voltage $v_o(t)$ corresponding to $di_p(t)/dt$. It can do so with a high dynamic range, making the voltage $v_o(t)$ proportionally larger as $i_p(t)$ increases. However, the integrator and the related signal conditioning circuits have finite operating ranges and cannot handle arbitrarily large $v_o(t)$ signals. For instance, if operated through supply rails of $V_H$ on the high side and $V_L$ on the low side, the signal conditioning can handle a peak-to-peak voltage swing of $V_H - V_L$. Any signal transitions above this can cause these circuits to saturate. This results in waveform clipping and distortions as shown in Fig. 4.10.
This means that even though a Rogowski coil transducer can be potentially used for measuring large current, the signal conditioning stage needs to be adjusted or ‘tuned’ for these current levels for maintaining signal integrity and accuracy. The same ‘tuning’ cannot be used for measuring lower currents—i.e. specific tuning required for different operating ranges, resulting in highly customized sensor design. In order to overcome this limitation, an adaptive signal conditioning stage is needed—one that scales itself dynamically to match the level of the current being monitored. To accommodate this, a three-stage analog signal conditioning stage (shown in Fig. 4.11) has been designed as discussed next.

4.5.3 Front End Amplifier

From Table 4.1 we observe that the mutual inductance of the Rogowski coil for physical dimensions discussed so far ranges from $10 \cdots 100 \text{nH}$ at $60 \text{Hz}$. This implies that the sensitivity of the coil is approximately $25.45 \mu V/\text{A}$ — a signal so weak, it cannot even be observed on an oscilloscope! Before integrating this signal, it is necessary to amplify it first and this is achieved through the front end amplifier.

Additionally, since the Rogowski coil output signal $v_o(t) = Mi/dt$ is weak, it is susceptible to being corrupted by noise. Typically, this noise can manifest as a common mode noise since it can affect either of the leads connecting the Rogowski coil to the signal conditioning stage. Thus, the front end amplification stage must have a good common mode rejection property. Further, the Rogowski coil does not have large signal sourcing.
capability, necessitating the use of a high input impedance stage for the front end amplifier. For this reason, an instrumentation amplifier with an ultra-low input bias current (0.15 nA) has been selected for the front end amplification. This stage removes any common mode noise, offset errors and unwanted stray signal couplings. Further, this instrumentation amplifier has been converted into a programmable gain stage through the use of solid-state analog switches as shown in Fig. 4.12.

The programmability and gain selection adds a dynamic range of $1:1000$, i.e. $+0$ to $+60$ dB right at the input.

### 4.5.4 Low Noise Integrator Stage

The integrator stage for a 60 Hz Rogowski coil sensor is the most crucial element for a successful sensor design. A low-noise, low-drift stage is necessary to ensure stable operation over long periods of time. Op-amps with an ultra-low offset voltage minimizes
Table 4.2: Integrator op-amp characteristics

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offset voltage</td>
<td>$\pm 5 \mu V$</td>
</tr>
<tr>
<td>Offset voltage Drift</td>
<td>$\pm 2 \mu V/^\circ C$</td>
</tr>
<tr>
<td>Noise Characteristics</td>
<td>$5 \text{ nV}/\sqrt{\text{Hz}}$</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>10 MHz Gain bandwidth product</td>
</tr>
<tr>
<td>Slew Rate</td>
<td>$20 \text{ V}/\mu \text{s}$</td>
</tr>
<tr>
<td>Bias current</td>
<td>$\pm 5 \text{ pA}$</td>
</tr>
</tbody>
</table>

the possible drift that can accumulate over time and appear as an error. For the power grid applications, the current sensor must function over a bandwidth of 20 Hz to 15 kHz, that accommodates $> 20$ harmonics. Additionally, it is necessary to ensure any remnant DC offsets are filtered out so that the resulting signal is free from any distortions. The specs are highlighted in Table 4.2.

4.5.5 Adaptive Programmable Gain Amplifier

In the final stage, a programmable gain amplifier (PGA) is used to condition the signal for the ADC. The digitally controlled PGA has a gain range from 0.125 to 176, adding another 1 : 1400 to the dynamic range (i.e. $-18$ to $+45 \text{ dB}$). In addition to the gain, this stage can level-shift the signal and centers it around either half of the voltage rail (+1.65
V) or around ground reference. This sets it up for both single ended (e.g. $0 - 3.3\, V$ ADC in MCUs) and fully differential ADCs (e.g. $\pm0.5\, V$ ADCs found in AFEs).

The controllable stage of the signal conditioning circuits (front end amplifier and the PGA) can be adjusted through GPIOs available on host MCU. The output is observed to settle within 400 ns of actuation from the MCU as seen in Fig. 4.18(a).

4.5.6 Analog to Digital Conversion

The current sensor can work with a variety of ADC architectures, like successive approximation ADCs, $\Sigma - \Delta$ ADCs, flash ADCs etc. If intended to be used with an analog-capable MCU, the ADCs embedded inside these MCUs/DSPs tend to be single ended successive approximation or flash ADCs. It is important to note that each ADC still has the dynamic range limitation illustrated in Fig. 4.10.

For demonstrating the proof of concept, the MCU chosen is the mixed signal processor MSP432P401R which has ultra-low power consumption, fast speed (48 MHz) and excellent ADC integration. The on-board ADC has a successive approximation architecture, featuring upto $200\, kS/s$ sampling rate. For the purpose of the experiment, it has been configured to sample at $10\, kHz$ and a $10 \times$ oversample and average architecture to generate and store the waveform data (16 samples/cycle) to the on-board flash memory in a cyclic memory buffer.

Performance with other ADC architectures is showcased in Chapter 5.
4.5.7 Overall sensor specifications

A summary of the sensor specifications can be found in Table 4.3. It can be concluded that the developed sensor can be useful for power line current measurement.

Table 4.3: Prototype sensor specifications

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rogowski coil sensitivity</td>
<td>0.42µV/A-Hz or 25.45µV/A @ 60 Hz</td>
<td>Rogowski coil’s sensitivity for generating $di/dt$ signals based on enclosed currents</td>
</tr>
<tr>
<td>Rogowski coil bandwidth</td>
<td>&gt; 10 MHz</td>
<td>No self resonance observed till 10 MHz</td>
</tr>
<tr>
<td>Signal conditioning bandwidth</td>
<td>20 Hz to 15 kHz</td>
<td>Accommodates 20+ harmonics at power line frequencies and can work with switching power supplies too</td>
</tr>
<tr>
<td>Settling time @ 60 Hz</td>
<td>40 ms</td>
<td>Integrator settling time when switching gain abruptly</td>
</tr>
<tr>
<td>Phase error @ 60 Hz</td>
<td>2°</td>
<td>Within metering grade accuracy</td>
</tr>
<tr>
<td>Settling time @ 600 Hz</td>
<td>9 ms</td>
<td>Integrator settling time when switching gain abruptly</td>
</tr>
<tr>
<td>Resolution</td>
<td>14-bit successive approximation ADC</td>
<td>Actual measurement resolution is governed by the gain setting and the DRC algorithm</td>
</tr>
<tr>
<td>Gain switching time</td>
<td>400 ns</td>
<td>Gain transition time satisfies high speed switching requirements</td>
</tr>
</tbody>
</table>
4.6 Dynamic Range Correction Method

In order to adjust the signal conditioning stage, a new method called ‘Dynamic Range Correction’ (DRC) has been developed and implemented.

![Figure 4.13: Illustration of ‘Dynamic Range Correction’. Output of sensor with and without DRC. Without DRC, sensor saturates at rail voltages, offering limited dynamic range during fault currents.](image)

The proposed ‘Dynamic Range Correction’ method can adjust the gain of the analog circuits so that the current being measured is mapped into the full scale range of the ADC (e.g. $0 - 3.3$ V), especially when the current changes drastically in fault scenarios. An illustration of this concept is shown in Fig. 4.13. Consider a current being measured and the analog signal conditioning stage tuned to the operating band at nominal levels. Consider a scenario where, due to faults or other such transients, the current changes suddenly from say $14$ A\(_{pk}\) to $400$ A\(_{pk}\). In this scenario, with a finite rail to rail swing on the analog integrator, the analog stage can saturate and clip the signal, resulting in distortion. However, if we were to dynamically adjust the gains of the analog stage, to match the current levels, the
analog signal can be ‘compressed’ to maintain the signal within rail to rail swing, and can be ‘uncompressed’ during post-processing.

This scenario is simulated and shown in Fig. 4.13. The orange trace shows the sensor output without DRC (status quo), which is corrupted due to signal saturation. However, if the gains of the signal conditioning stage were to be controlled as shown by the blue trace, the signal can be compressed and the waveshape preserved. Later, during post-processing, the signal is reconstructed, as shown in the green trace.

This method effectively creates a one-on-one mapping between the input current $i(t)$ and the sensor output voltage $v(t)$ and can be used to switch the gains as shown in Fig. 4.14. However, magnitude alone cannot be used for range correction since it can lead to chattering and hence the $di/dt$ information is also used, as explained next.

Figure 4.14: Typical sensors will saturate around $3 − 5$ V, which is the full scale of the ADC. With DRC, the gain is adjusted to map the current waveform to the full scale range of the ADC.

Consider a steady state input current $i(t)$ flowing in the utility conductor. From (4.7) voltage induced in the Rogowski coils is $v_o(t) = M.di(t)/dt$. The integrator with a gain $G$ produces an output:

$$v(t) = \int G.M.\frac{di(t)}{dt} = G.M.i(t) \Rightarrow \frac{dv}{dt} = K \frac{di}{dt} \quad (4.13)$$
Based on the calculated value of $dv/dt$ as shown above, gain $G[n+1]$ is adjusted so that the raw sample value $v[n]$ is maintained between 0 and 3000 mV to avoid distortion. It can be seen that the integrator output $dv/dt$ is related to the incoming $di/dt$ through a constant, $K$ which is the overall gain of the system. Thus when the incoming $di/dt$ changes drastically in the event of a fault, the MCU can calculate $dv/dt$, and knowing the gain of the integrator, estimate the current level on the primary conductor. Based on these values, a new gain is calculated so that the analog stage does not saturate, as shown in Fig. 4.15.

In reality, the $dv/dt$ is calculated in the discrete domain by $dv/dt = (v[n] - v[n-1]) \cdot f_s$ where $f_s = 10$ kS/s; and used to generate the next gain value $G[n+1]$, which depends on the present gain value $G[n]$, the RMS trend of the voltage $v_{rms}$ and the calculated $dv/dt$. Besides, there exists a pre-set mapping of gains corresponding to different current levels for which the current variation maps into the full scale range of the ADC.

For instance, $i(t) \in [1, 10]$ A $\implies dv/dt \in [K \omega, 10.K \omega]$; $i(t) \in [10, 100]$ A $\implies dv/dt \in [10.K \omega, 100.K \omega]$ and so on. The MCU then sets the gain $K$ so that $v[n+1]$
will be maintained within 0 – 3.3 V. This procedure is summarized in the algorithm 1.

Thus the sensor can intelligently detect high $di/dt$ signals and adjust the gain to obtain full scale mapping to the ADC.

Algorithm 1 Algorithm for Dynamic Range Correction

*Input from ADC:* Sample at the $n^{th}$ instant, $v[n]$

*Input from Memory:* $N$ previous samples: $v[n-1], v[n-2]...v[n-N]$

**Repeat:**

1: Use $v[n]$ and $v[n-1]$ to compute $dv/dt$

2: Calculate $di/dt$ using $dv/dt$ and present gain $G_i$

3: Use \{ $v[n], v[n-1]...v[n-N]$ \} to find $v_{rms}$

4: Use $v_{rms}$ and $G[n]$ to find $i(t)$

5: Using $di/dt$, $G[n]$ and $i(t)$ classify $i(t)$ into normal mode or fault mode

6: if fault mode then

7: Pick appropriate lower gain for $G[n+1]$ corresponding to $di/dt$ computed

8: Trigger a waveform capture mode & save sampled data to special section of memory

9: else

10: Ensure $G[n+1]$ is suitable for present $i(t)$

11: end if
4.7 Experimental Validation

![Figure 4.16: (a) Test schematic, (b) Setup and (c) Manufactured prototype with different sections labelled.](image)

To test the performance of the clip-on Rogowski coil interfaced with the DRC integrator signal conditioning stage, the signal conditioning stage was manufactured on a compact 6 cm $\times$ 6 cm PCB. The bench-top test setup is shown in Fig. 4.16. A Pearson current probe [170] was used as a reference measurement to validate the performance of the proposed sensor.

4.7.1 Transient Response of the Current Sensor

For capturing faults or currents with large transients, the signal conditioning stage must respond with a fast settling output. However, the crucial element that can have delays in the settling time is the integrator stage. Thus, the integrator stage must be adjusted for fast transient response, ideally settling to the expected values within a few line cycles (i.e. within $\sim$ 50 ms), and not having a large overshoot. Fig. 4.17 shows the simulated and experimental transient responses of the integrator stage to $di/dt$ signals at 60 Hz and 600 Hz. It can be seen that the integrator transient settles within 2 – 5 cycles over a bandwidth accommodating 10 harmonics, without significant phase error.
Figure 4.17: Transient response of the integrator (a) SPICE simulations at 60 Hz (b) Hardware tests at 60 Hz (c) SPICE simulations at 600 Hz (d) Hardware tests at 600 Hz. As seen in the hardware tests, the integrator (red trace) settles in $2 - 5$ cycles when a simulated fault current $di/dt$ input (green trace) is applied.

The controllable gain stage also has a quick actuation time, responding within 0.5 $\mu s$, maintaining the overall signal integrity. This response is shown in Fig. 4.18.
4.7.2 Frequency Response

The response of the sensor at various frequencies is shown in Fig. 4.19. As seen, the sensor output tracks the current waveform as expected, with a phase error < 2° at 60 Hz. Measured bandwidth is observed to be between 20 Hz and 15 kHz, accommodating good harmonic content for analyzing faults in power conductors. Besides, the gain response can be dynamically adjusted using DRC as shown next.
Figure 4.19: Sensor output at various frequencies: 60 Hz, 600 Hz, 6 kHz, 60 kHz sinusoidal excitation and at 15 kHz square and triangular wave excitation.

Figure 4.20: Frequency response of the sensor from $i_p(t)$ to sensor output $v(t)$. Note that the magnitude response can be adjusted by DRC.
4.7.3 Dynamic Range Correction

For higher currents, a current circulating loop was created as shown in Fig. 4.21. The sensor output at various current levels is shown in Fig. 4.22, with the output always being within ADC full scale range.

![Diagram of current sensor and circulator setup](image)

Figure 4.21: Setup to circulate high current in a loop. A comparison of the form factors of Pearson current probe [170] and proposed sensor is shown.

Test results from the DRC algorithm are shown in Fig. 4.23, where \( \frac{di}{dt} \) signals corresponding to different fault current levels are applied and varied with time. The sensor adapts the gains to keep the analog output within the full scale of the ADC, without any distortion. The sensor output is effectively compressed from \( t = 15 - 75 \) s and uncompressed from \( t = 75 - 115 \) s as seen from the discrete ADC output.
Effectively, the sensor can measure currents from 25 mA up to 50 kA without saturation or distortion. Thus, a dynamic range of $1 : 2,000,000$ has been achieved by the proposed DRC approach. Compared to the state-of-the-art Rogowski coil sensors, this im-
Figure 4.24: Fault current capture from 410 $A_{rms}$ steady state to $\sim 21$ kA$_{rms}$. (a) Oscilloscope waveforms (b) ADC sampled data on the sensor (c) Reconstructed waveform.

Improvement in dynamic range can enable the same sensors to be used for measurement of nominal operational currents, as well as capturing the occasional fault waveform. This also allows the same sensor to work across a broad operating range without the need for configuring the hardware to ‘match’ currents being monitored.

Next, a transient test was carried out using only $di/dt$ signals corresponding to different fault currents. A $di/dt$ signal corresponding to 410 $A_{rms}$ steady state was applied and then switched to the $di/dt$ level corresponding to 21 kA$_{rms}$ fault current state as shown in Fig. 4.24. The sensor intelligently adjusts the gain to maintain signal integrity and prevent distortion as seen from the ADC sampled signal in Fig. 4.24. The waveform is reconstructed by the sensor and streamed to a computer for visualization as shown in Fig. 4.24. Similar test showing recovery from a 50 kA$_{rms}$ fault current to the 330 $A_{rms}$ steady state is shown in Fig. 4.25.

Further, to prove that the Rogowski coil and the DRC integrator does not saturate at a high current level, an impulse test was carried out using the setup shown in Fig. 4.26. A capacitor bank (1 mF) was discharged into the primary winding of a 50 : 1 turns-ratio co-
Figure 4.25: Fault recovery from 50 kA\textsubscript{rms} to 330 A\textsubscript{rms}. (a) Oscilloscope waveforms (b) ADC sampled data on the sensor (c) Reconstructed waveform.

Figure 4.26: Setup to generate high current impulse using a co-axial winding transformer (CWT). The thyristor was triggered to discharge the capacitor into the primary (50 turns) of the CWT with the single secondary turn shorted, generating an impulse of 19 kA\textsubscript{pk}. 
axial winding transformer (CWT). The secondary terminal was shorted to generate a high impulse current across the single turn and the proposed sensor clipped-onto this terminal as shown in Fig. 4.26.

The resulting \( \frac{di}{dt} \) signal generated by the clip-on Rogowski coil, and the integrated sensor output are shown in Fig. 4.27. As observed, the sensor output does not saturate and is free from any distortions.

### 4.7.4 Noise Analysis and Auto-triggering Gain Adjustment

A possible alternative approach for dynamically adjusting the individual gains of the signal conditioning stage would be to use the \( \frac{di}{dt} \) signal directly. Level-triggered circuits can be designed to switch gains when the incoming \( \frac{di}{dt} \) signals (the output of the Rogowski coil) vary beyond certain thresholds. However, a careful look at the noise-spectra at individual stages reveals that this is in fact, infeasible.

The signal to noise ratio (SNR) at the output of the Rogowski coil sensor is only 20 dB at 60 Hz i.e. the \( M \frac{di}{dt} \) signal is only 20 dB above the noise floor when \( i_p = 2.67 \, \text{A}_{\text{RMS}} \). The signal is not strong enough to guarantee auto-triggering if it were to be used to drive a gain switching stage before the integration stage. Since the coil itself has a +20 dB/dec gain response, we see that the SNR improves at higher frequencies.

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Figure 4.27: Output of the sensor during pulse test. Sensor does not saturate at high impulse current.

---

\(^2\)This setup is attributed to Sathish Jayaraman and Rohit Jinsiwale, graduate students at CDE
Figure 4.28: Noise spectra at various stages of the sensor system. The $di/dt$ signal itself, at the output of the Rogowski coil has a very poor SNR ($\sim 20$ dB). This makes it infeasible to use the incoming $di/dt$ signal itself for dynamic range correction.

As seen in Fig. 4.28, the combined analog stages ensure a flat gain response across the bandwidth of interest and the overall system is able to achieve the same signal to noise ratio (SNR) of $\sim 75$ dB at the input of the ADC, across all frequencies. In the signal chain, the SNR at 60 Hz is seen to improve from 20 dB to 76 dB.
4.7.5 Immunity to Drift Errors

The prototype was operated continuously over 48 hours in order to quantify the drift errors in the system. Over this extended run, the system output had a drift of 0.1 mV in the output, and a 0.1° drift in phase. This has been resolved by periodically resetting the integrator so that the errors do not accumulate significantly. In the present system, the MCU is responsible for shutting down the front-end amplifier and the adaptive PGA, thereby driving the integrator output to zero and resetting it.

4.7.6 Immunity to External Interference

Since Rogowski coil sensors completely encircle the conductor, they are relatively immune to the stray magnetic fields produced by conductors around them [88]. This can be seen by the definition of mutual inductance due to external current-carrying conductor, $M_{ex}$.

$$M_{ex} = \frac{d\phi_{ex}}{di_{ex}} = \frac{d(\sum_{j=1}^{N} \int c A_{ex}^{j} \cdot dl)}{di_{ex}}$$  \hspace{1cm} (4.14)

where $N$ is the number of turns in the coil, $A_{ex}^{j}$ is the vector potential field over the $j^{th}$ turn (for details, refer to [88]). It can be seen that since the encircled area becomes zero as $N$ becomes large enough, $M_{ex} \approx 0$.

To verify this, an experiment to quantify the external interference was conducted using the setup shown in Fig. 4.29.

Table 4.4: Results from interference test

<table>
<thead>
<tr>
<th>$i_1$</th>
<th>Output (mV$_{rms}$)</th>
<th>$i_2 = 0$</th>
<th>$i_2 = 1$ A</th>
<th>$i_2 = 5$ A</th>
<th>$i_2 = 10$ A</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 A</td>
<td>131</td>
<td>131</td>
<td>131</td>
<td>130</td>
<td></td>
</tr>
<tr>
<td>5 A</td>
<td>742</td>
<td>742</td>
<td>742</td>
<td>742</td>
<td></td>
</tr>
<tr>
<td>10 A</td>
<td>175</td>
<td>175</td>
<td>175</td>
<td>175</td>
<td></td>
</tr>
</tbody>
</table>

As seen from Table 4.4, the effect of interference, in the worst case (i.e. when $i_2/i_1 = 10$) is less than 0.8%, which is consistent with the findings in [88].
Figure 4.29: Setup to perform interference test. $i_1$ is the current being measured and $i_2$ is the external noise source, placed at a distance of 5 cm from the Rogowski coil.

4.8 Design of a Current Sensor with Universal Form-Factor and Adaptable Design

In order to create a flexible current sensor prototype, an adaptable version of the Rogowski coil-based current sensor and the DRC integrator has been developed. Two applications are envisioned–

1. A current sensor to be used within a more complex application like an asset monitor or a smart meter. These applications typically use an application-specific AFE. For example, smart meters will use an energy metering AFE. These AFEs tend to have a specific signal input range that is acceptable and can tolerate very low common mode voltages (e.g. $\pm 0.5 \text{ V}$ with a common mode tolerance of $\pm 50 \text{ mV}$). This application needs some form of interface between the current sensor and the application MCU, which may have limited I/Os.

2. A stand-alone current sensor with its own MCU and full control logic. This type of application would typically leverage the MCU’s own ADC sub-system, which typically accepts analog voltages ranging from $0 - 3.3$ or $0 - 5 \text{ V}$. In these type of applications, when the MCU’s ADC cannot digitize voltages less than 0 V, the
sensor output needs to be level shifted and conditioned before interfacing with the MCU ADC.

For this, a prototype which integrates the PCB-based Rogowski coil and the active DRC integrator stage has been designed and fabricated. The integrator stage offers the flexibility in selecting the common mode reference and the choice between a single-ended output stage, or a fully differential output signal pair.

The mechanical casing around the sensor converts it into an open-jaw configuration\(^3\), pivoting around one end and clipping to encircle the conductor in the field through a weather-proof connector on the other end. The final sensor packaging is shown in Fig. 4.30.

![Figure 4.30: 3-D printed package and PCB for the current sensor](image)

(a) Final packaging, (b) Assembled PCBs.

The adaptability of the manufactured hardware makes the sensor compatible with the two approaches discussed above. One application would be to integrate the current sensor into a system with more sophisticated data acquisition stage as discussed in the next section.

\(^3\)The mechanical design for the 3-D printed package is attributed to Brandon Royal and Zachary Laird of CDE

135
chapter. This is shown in Fig. 4.31(a). In the other approach, an independent current sensor has been envisioned, for overhead distribution feeder conductors. In this case, the sensor can be powered through a combination of PV + battery system while interfaced with an MCU ADC with an embedded GAMMA Kernel.

Figure 4.31: Adaptable hardware that can be utilized with different types of applications.
CHAPTER 5

SMART SENSOR FOR MONITORING DISTRIBUTION TRANSFORMERS

5.1 Introduction

In this chapter, we examine the design of a smart transformer monitoring sensor\(^1\), based on GAMMA platform and the novel Rogowski current sensor. Broadly, we develop a sensor that can record sub-metering type data which can be used for obtaining operational insights into the network.

Low-cost asset monitoring can be a key enabler for utility operators to gain advanced visibility into the network, maintain reliability of the deployed fleet and avoid catastrophic failures. With widespread AMI deployment, the utilities are beginning to get inundated with lot of granular data which can be leveraged to perform diagnostics and advanced tasks like asset health management. However, the costs associated with deriving meaningful insights and consequently value from the AMI ‘data ocean’ is prohibitive and a major hurdle for average U.S. utilities\(^2\).

For asset monitoring, an important distinction can be made with respect to the data being recorded. Over most of the useful life of the asset, the data recorded would fall within the recommended operating bounds of the asset. These data do not provide any important insights into the asset’s health in a business as usual scenario. However, in the rare occurrence when certain anomalies occur in the grid— a downstream fault, a power flicker or abnormal harmonics due to unconventional loads etc. It is important to capture and quantify these type of disturbances to alert the utility operators about potential damaging events. These events can manifest as a result of underlying issues with the asset itself, or broader

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\(^1\)This project, “SENSE— Sensing Electrical Networks Securely & Economically”, has been funded by U.S. Department of Energy for developing a scalable solution for monitoring distribution transformers, in partnership with Southern Company and Oak Ridge National Lab.
operational issues in the system. Sensors that can distinguish between normal modes of operation and these anomalies through edge-intelligence can help in delivering targeted, key insights to the utility operators, so that the system is not overwhelmed with gigabytes of data, but rather, few critical snippets of information that reveal the key parameters.

In literature, several specialized experimental and commercial sensor solutions have been developed as discussed in Chapter 2. These are mostly based on traditional IoT-based approaches of connected sensor pushing data to the cloud and relying on cloud-based computing to extract meaningful insights.

A viable ‘intelligent’ sensor for service transformers must look at all relevant parameters (like voltage, current, power and temperature) for a transformer holistically. However, we find that the sensors proposed in literature lack at least one of the following attributes that are necessary for the viable sensor design—

1. The sensor must be low-cost and easy to install

2. The sensor must function in arbitrary locations without relying on constant cloud-based communication

3. The sensor must record data and perform analytics locally to extract important features or anomalies to be reported to the cloud

To address these challenges, a low-cost transformer monitoring sensor design has been proposed, based on the Rogowski-coil current sensor and GAMMA platform discussed previously. The sensor, equipped with multiple sensing modalities, can look at the transformer as a whole and record anomalies or outliers which fall outside of the normal operating ranges and aggregate such data captures. With the help of local data processing, the sensor can extract meaningful information to be reported to the cloud on a priority basis. With these ‘actionable’ insights, the utility operators can obtain more visibility into the types of events that can cause increasing operational stress on the transformer, eventually leading to loss-of-life.
One of the major causes of damage to distribution transformers is sustained overloading and frequent downstream faults, causing damage to internal winding insulation. The damaged insulation creates an internal hotspot and heating, which further exacerbates the deterioration. For an asset monitoring sensor, it is imperative to distinguish between normal mode of operation and these abnormal ‘events’ and intelligently capture relevant information pertaining to the event.

The current sensor technology discussed so far, has been leveraged to develop a low-cost asset monitoring solution for pole-top distribution transformers. The split-single phase (±120 V_{ac} and Neutral) transformer is the target application for the device. The clip-on nature of the current sensor allows non-intrusive sensing and quick installation in the field. The DRC method described so far enables two things—

- The ability of the same sensor to be used for different assets with varying power (current) levels.
- The ability of the sensor to detect faults and capture waveforms for the faults.

The transformer monitoring device is essentially a split-single phase sub-metering device based on the novel current sensing technology. A GAMMA Kernel operates as the edge-intelligent node and is responsible for managing the data storage, communication and other housekeeping activities.

The sensor detects anomalies worthy of being reported to the operators, performing intelligent data extraction and analysis at the edge of the network. In addition to detection of anomalies, the sensor looks at multiple physical quantities and records time-stamped data, storing it locally. Upon request, the sensor can uplink the data to the cloud where it can be used for standard, cloud-based analytics like those proposed in literature.
5.2 Hardware Architecture

The hardware architecture of the transformer sensor is shown in Fig. 5.1. The sensor consists of two PCB-based Clip-on Rogowski coils, based on the universal AC current sensor design explained before. The current sensor is configured in a differential output mode for a 0 V common mode signal. The current sensor is interfaced with a single-phase energy metering AFE capable of recording currents on two channels. The two channels correspond to the two phase lines supplied by a North-American pole-top, split-phase service transformer.
The current sensor interface is shown in Fig. 5.2 and corresponds to the architecture introduced in Fig. 4.31(a) previously. The energy metering AFE (ADE7983) [185] hosts a 24-bit $\Sigma - \Delta$ ADC architecture, clocked at 895 kHz with a feedback loop that generates a 24-bit stream representative of the averaged value\(^2\) of the input signal. The $\Sigma - \Delta$ ADC has an oversampling and noise shaping functionality as the sampling frequency is 895 kHz, but the bit stream is generated at a 6.99 kS/s interval. The external, packaged clip-on Rogowski current sensor is connected through a multi-conductor, shielded cable assembly as shown in Fig. 5.2 and 5.3.

The sensor is powered directly from the low-voltage ($240 \text{ V}_{ac}$) terminals from the transformer. The sensor hosts an isolated AC/DC converter which powers the complete unit, generating the $+5 \text{ V}$ and subsequently a $+3.3 \text{ V}$ DC voltage rail. The hardware hosts a Li-ion battery charger with the aim of retaining charge when power outages occur. The hardware also has provisions for interfacing an external PV panel to trickle charge the battery in times of prolonged outages.

The system has two co-processors— the MSP432 and the CC2640R2F (hosted on the GAMMA Kernel). The MSP432 is responsible for interfacing with all the transducers and periodic data collection and analytics, while sending the data over a digital SPI link to

\(^2\)The digital LPF averages the incoming bit stream
the GAMMA Kernel. The GAMMA Kernel acts as the communication controller, hosting the BLE transceiver. The GAMMA Kernel also stores the time-stamped data locally in the GAMMA memory buffer, ready to be uplinked whenever requested by the GAMMA Server through a data mule.

The AFE is responsible for energy (active, reactive and apparent) measurement and associated computation based on the digitized bitstream for $v(t)$ and $i(t)$ produced by the $\Sigma - \Delta$ ADCs. This is done over a cycle-by-cycle basis as follows—

$$P = \frac{1}{nT} \int_{0}^{nT} \sqrt{2} V_{rms} \sin(\omega t) \sqrt{2} I_{rms} \sin(\omega t + \phi) dt$$

(5.1)

$$P = \frac{V_{rms} I_{rms}}{nT} \int_{0}^{nT} \{(1 - \cos(2\omega t)) \cos \phi + \sin(2\omega t) \sin \phi \} dt$$

(5.2)

where, $P$ = active power, $n = \text{number of line cycles}$, $T = \text{time period of line cycles (20 ms or 16.67 ms)}$. Since $\cos(2\omega t) \& \sin(2\omega t)$ integrate to 0 over integer number of cycles, we get $P = V_{rms} I_{rms} \cos \phi$. 

142
In the digital domain, \( V_{rms} \) and \( I_{rms} \) are the root mean square values of voltage and current waveforms, calculated from the discretized signals as follows:

\[
V_{rms} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} V_n^2} \quad \text{and} \quad I_{rms} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} I_n^2}
\]  

(5.3)

\( N \) is total samples, \( V_n, I_n \) are (discretized) voltage & current.

In the present system, power is averaged over fixed periods \( T \), each of 4.83\( \mu \)s, which gives us the energy consumption \( E = \sum_{k=1}^{\infty} P_k \cdot T \) where \( P_k = k^{th} \) power sample.

In addition to the energy metering interface, the sensor hosts two temperature sensors for measuring the ambient temperature and the transformer tank temperature. The ambient temperature is measured through an IC-based analog temperature sensor mounted on the main PCB. The tank temperature is measured through an infra-red, compensated thermopile. The thermopile lens is pointed towards the transformer tank temperature through a small window drilled into the sensor enclosure. The rich data capture allows data analysis locally, at the edge as well as in the cloud, based on fleet measurements.

The sensor also hosts a MEMS based accelerometer that provides an analog output proportional to the acceleration the system experiences. The sensor is capable of recording a resting state (gravitational) acceleration output as well, and this is leveraged to determine the tilt of the pole or any sudden change in the orientation of the sensor. The manufactured transformer sensor is shown in Fig. 5.3.

5.3 Software Architecture, Data Management and Communication Engine

The software suite in the smart transformer monitor has been implemented on the two co-processors, both using TI-RTOS adopted for the respective embedded processors— the GAMMA Kernel running the GAMMA stack, while the MSP432 implementing the software for the transformer sensor. The software suite is event-driven with the co-processors signalling each other through a combination of GPIO and SPI handshaking.
The sensor begins functioning once installed in the field and commanded with a ‘commissioning’ packet that originates from a utility personnel’s smart phone (data mule) which delivers an encrypted packet to the GAMMA Kernel over BLE. Once the Kernel interprets the packet, it signals the co-processor to commission the device and the co-processor begins data collection.

In the data collection phase, the MSP432 reads the energy metering AFE’s internal registers to obtain voltage, current (2 values, one for each phase) and energy (4 values, active and apparent for both the phases). This data point is generated every 1 minute. Every 15th minute, the MSP432 aggregates the last 15 data points and generates an average voltage, aggregated apparent and active energy (each phase) and reads the ambient and case temperature from the analog sensors and ensures that the pole-tilt has not changed over time. This aggregated data point is pushed to the GAMMA Kernel, where it is stored in the Kernel’s external flash memory along with a time stamp. This continues on every 1 and 15 minute horizons.

Every time a fault or an abnormality occurs, the metering AFE interrupts the MSP432
processor, which proceeds to gather further information about the event. This is in the form of a waveform snippet or an aggregated value (magnitude) and duration of the event. These events can happen in an asynchronous fashion, and the generated data point is transferred over to the GAMMA Kernel over the SPI bus, where it is stored in the special, high-priority section of the flash memory.

The GAMMA Kernel keeps advertising itself to the available data mules, who can discover and connect with it. If a connection is established over BLE, depending on the last time data from the device was reported to the cloud server, the server can request the sensor to report all data collected between two arbitrary time stamps $T_1$ and $T_2$ (as determined by the server or the utility operator). Once the Kernel receives this ‘command’ it searches for these data in the memory, retrieves them and uplinks them to the cloud through the data mules, in a latest-first manner. The events (i.e. anomalies) are given a higher priority over regular, time series data. This process has been captured in Fig. 5.4.

The smart transformer sensor can thus generate time-stamped, sub-metering data at 15 minute intervals. The 15 minute interval was chosen to match the AMI network’s data reporting frequency. In reality, an arbitrary number could be chosen— as high as a data point every 2 sec, to as low as a data point every 1 day. With the GAMMA communication and data management engine embedded into the sensor, the overall communication requirements become very lean. Utility operators may not be interested in the raw, time-stamped information in business as usual case but only the abnormalities representative of any incipient or underlying system issues. On the other hand, the data points are stored locally and are available if the utility operators need to perform a post-event analysis. These recorded abnormalities can be reported on a priority basis through data mules, while storing the other raw data at the edge of the network. This time series data is also analyzed over longer time horizons to extract some patterns of interest that can be reported to the utility operators, as described in Chapter 6.
5.4 Performance Evaluation

The performance evaluation of the fabricated prototype is described next.

5.4.1 Voltage, Current and Energy Measurements

![Circuit diagram](image)

Figure 5.5: Experimental setup for validating the sensor performance (a) Circuit diagram, (b) DUT transformer with sensor mounted, (c) Close-up of the sensor.

In order to test the measurement accuracy and characteristics of the sensor, a transformer test setup was created at the Center for Distributed Energy High Voltage cell. The test setup is shown in Fig. 5.5. Two 50 kVA transformers were connected to each other through a 100 kVA variac. The transformer monitor was installed on the DUT, while the other transformer (AT—Auxiliary transformer) was not instrumented. The variac was controlled to create a $1 : N$ voltage shift, which created a circulating current loop between the two transformers as seen in Fig. 5.5.

The turns ratio of the variac was steadily changed to get a varying circulating current. In this configuration, the current could be steadily varied from 50 mA to $\sim 220$ A. This setup was used for validating the sensor’s steady-state current measurements. The sensor

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3This setup was developed for the SENSE project with the help of Brandon Royal, Prasad Kandula and Kavya Ashok

146
dynamically adjusted the signal conditioning stage to record a 1-min averaged RMS current value. The variation of the gain switching (red trace) and the error (absolute error in Amps, pink trace) trend with respect to the changing input current are shown in Fig. 5.6. These measurements were recorded against a combination of a 400 : 5 A CT along with the 0.1 V/A Pearson sensor, interfaced to an Oscilloscope.

The actual sensor response is shown by the blue dots, while the expected linearity curve is depicted in black. As observed in Fig. 5.6, the overall error is ~ 1% across the operating range. This validates the auto-tuning mechanism which enables the same sensor to measure currents across a wide operational range without compromising accuracy.

The voltage measurement across the entire possible operating range has been recorded in Fig. 5.7. The black trace shows the expected linearity curve and the blue records the sensor measurements. The red trace is the absolute voltage error (in Volts) while the pink trace records the % error in the voltage measurement. The voltage measurement error across the entire operating range is ~ 0.2%.
Further, the setup shown in Fig. 5.5 was also used to validate the energy accumulation at different operational points under steady-state conditions. Fig. 5.8 shows a few recorded data points on the sensor across different voltage and circulating current values. The oscilloscope captures show voltage waveform recorded in the setup in the green trace, while the circulating current in the pink trace under different conditions like different voltages, loading levels and even phase angles between the voltage and the circulating current.

The sensor was configured to accumulate the energy consumption and generate a data point in every 4 sec interval. Fig. 5.8 shows the values (voltage, current, power factor and, apparent energy (in kW-hrs)) expected based on Oscilloscope measurements and the measurements recorded by the sensor. The recorded data can be seen to be within expected bounds.

The above experiments demonstrate a highly accurate, energy sub-metering device.

5.4.2 Temperature Measurement

The transformer tank temperature sensor, based on an IR-thermopile sensor, aggregates all the radiated IR electro-magnetic energy and produces a voltage output that is proportional to the material surrounding the sensor’s window. Since the IR temperature sensor is pointed towards the transformer’s tank, the output is reflective of the tank tem-
Figure 5.8: Current (pink trace) and voltage (green trace) waveforms and corresponding measurement data recorded by the sensor.

5.4.3 Pole tilt detection

The smart transformer sensor hosts a 3-axis MEMS accelerometer which is leveraged to determine the tilt of the pole and flag if the tilt changes beyond a few degrees. The sensor produces an analog voltage that is proportional to the acceleration experienced by
the package and can be digitized through the MCU’s ADC. The output varies if the overall sensor package experiences shocks or vibration.

In steady state, the output also recognizes gravitational acceleration which has been leveraged to determine the 3-D orientation of the sensor with respect to the Earth’s gravitational field. If \(a_{x1}, a_{y1}\) and \(a_{z1}\) are the average values of accelerations recorded by the MEMS sensor in the three directions X, Y and Z at time \(t_1\) and \(a_{x2}, a_{y2}\) and \(a_{z2}\) are the corresponding values at time \(t_2\), then the angle of tilt \(\theta\) between the time instants \(t_1\) and \(t_2\) is given by—

\[
\theta = \arccos \left\{ \frac{a_{x1} \cdot a_{x2} + a_{y1} \cdot a_{y2} + a_{z1} \cdot a_{z2}}{\sqrt{a_{x1}^2 + a_{y1}^2 + a_{z1}^2} \cdot \sqrt{a_{x2}^2 + a_{y2}^2 + a_{z2}^2}} \right\}
\]

Whenever this angle between consecutive time instances varies within ±5° or if the difference between the present tilt vector \(a_{xn}, a_{yn}\) and \(a_{zn}\) and the tilt vector recorded during commissioning is more than ±5°, then an alert is raised for the utility operators.

Another application of the MEMS accelerometer is to record vibration signatures on the transformer tank. When a transformer undergoes degradation due to fault current or other electro-mechanical shocks, the transformer’s structural integrity changes, and this is reflected in the spectral decomposition of the vibration signatures recorded on the tank. With the proposed sensor, it is possible to record, analyze and extract these vibration signatures.

\footnote{For details behind the theory and experimental validation, the readers are encouraged to refer to [184]}
5.5 Operational Overview and Field Validation

The same GAMMA data mule mobile application can be used for commissioning the transformer monitoring devices in the field. Once installed in the final location and energized, the sensor begins advertising its presence as shown in Fig. 5.9. A trusted partner (e.g. utility technician) who has the data mule application on the phone, along with the necessary authorization, begins the commissioning process. A QR code is scanned and a secure⁵ commissioning packet is fetched from the GAMMA cloud, and downlinked to the sensor in the field. Once this command is received, the sensor generates and acknowledge ment packet, begins functioning and gathering data in the field.

A representative snapshot of data displayed in the GAMMA mobile phone application⁶ is shown in Fig. 5.10. The user can toggle between the different captured measurements and can visualize the same across different time horizons if the data exists in the back end. The app can also be used to request recorded data from specific time intervals

⁵Encrypted with a unique AES-128 key, hence encrypted end-to-end
⁶Development of the mobile application is a team effort attributed to GAMMA software team

Figure 5.9: Illustration of the sensor commissioning process.
from the individual sensors.

Figure 5.10: Screenshots showing transformer sensor data displayed in the GAMMA mobile application— (a) Case and ambient temperatures, (b) Active and apparent energy, (c) Voltage.

The GAMMA data mule app can also decommission specific devices in the field in a manner similar to the commissioning process. Thus, the GAMMA platform and architecture have been instrumental in enabling sensors to be quickly installed, commissioned and operated in the field, without the need for setting up complex communication infrastructure around it. The platform offers a secure channel for communicating with each distributed device in the field through the mobile phone application acting as a data mule.

Two fabricated prototypes were demonstrated in partnership with Center for Distributed Energy’s utility partners, Southern Company\(^7\) at their distribution test facility. The devices were installed on transformers in the field as shown in Fig. 5.11. The devices are

\(^7\)The author expresses gratitude towards the utility crew and team for working with CDE during the validation phase
commissioned through the GAMMA mobile application and get activated upon the receipt of an authorized command. Unit #2 was validated by the utility crew in the field using a controllable load bank.

A summary of the specifications for the transformer sensor can be found in Table 5.1.
### Table 5.1: Smart transformer sensor specifications

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Acquisition Stage</td>
<td>ADE7953 [185] AFE</td>
<td>3 channels, 895 kHz Σ − Δ modulator downsampled to 6.99 kS/s</td>
</tr>
<tr>
<td>Resolution and Bandwidth</td>
<td>24-bit, 1.23 kHz on each channel</td>
<td>Revenue grade AFE</td>
</tr>
<tr>
<td>Current Measurement</td>
<td>50 mA to ∼ 2 kA rms</td>
<td>Measured on two phases through the universal AC current sensor</td>
</tr>
<tr>
<td>Current Measurement Error</td>
<td>&lt; 1%</td>
<td></td>
</tr>
<tr>
<td>Voltage Measurement</td>
<td>105 to 300 V rms</td>
<td>Direct connection to transformer secondary</td>
</tr>
<tr>
<td>Voltage Measurement Error</td>
<td>&lt; 0.5%</td>
<td></td>
</tr>
<tr>
<td>Ambient Temperature Measurement Range</td>
<td>−50° to +150° C</td>
<td>Measured by a PCB-mount IC-based temperature sensor</td>
</tr>
<tr>
<td>Transformer Tank Temperature Measurement Range</td>
<td>−40° to +105° C</td>
<td>Non-contact IR temperature sensor</td>
</tr>
</tbody>
</table>

#### 5.6 Ecosystem of Low-cost Intelligent Sensors at the Grid Edge

This chapter presented the design of a low-cost sensor that has been developed for monitoring pole-top distribution transformers. The sensor network architecture is based on the previously discussed GAMMA platform and is specifically designed keeping in mind the application requirements for the distribution system assets. The novel Rogowski coil-based current sensor discussed in Chapter 4 forms the basis for non-intrusive current measurements in the developed prototype. This showcases the extent to which the current sensors can be used in more complex, sensor applications.

The sensor hardware, designed to be quickly installed on transformers in the field, can operate with a wide range of sensing modalities— including measurements of current, voltage, power/energy, temperature and changes in pole tilts. The sensors communicate through the GAMMA data mule app in a delay tolerant fashion. They can also be configured and commissioned in the field through the same app.
In addition to storing time-stamped, business-as-usual data, the sensor is configured to recognize anomalies that fall outside the normal operating bounds, which may be worth reporting to the utility operators. This is possible due to the integrated ‘edge-intelligence’ enabled by GAMMA platform. In the next chapter, a few examples of edge-intelligence-driven integrated analytics are discussed.
6.1 Introduction

In the distribution system, GAMMA platform has introduced a novel information processing architecture that allows all the granular data to reside at the edge of the network, in the sensor itself. With the smart edge computing node introduced earlier (e.g. GAMMA Kernel), it becomes possible to analyze this information locally, transforming each sensor into an intelligent edge computing node. The challenges and limitations of traditional architectures have been overcome by introducing a radically new communication and computational architecture that is well suited for distribution system analytics.

The integrated analytics in the proposed sensor is aided by ‘edge-intelligence’ viz-the ability for sensors, edge devices and distributed nodes to identify, compute and extract certain key features from the recorded data sets, based on pre-programmed rules as desired by the network operators. The edge-devices are designed to autonomously work in an ‘offline first’ environment without constant communication with the cloud server. The devices are capable of maintaining their operational states, measurements, and recorded data sets locally over long time periods, without having to communicate with the cloud.

The target applications for data analytics supported by smart sensors are those that use locally sensed data, without having to rely on data aggregated from multiple sensors or knowing other features like detailed network and topology information. These applications could range from time-series analysis of power profiles, identifying rule-based violations of certain operating conditions (e.g. faults) or quantitative analysis of captured data (e.g. harmonics or distortion or estimation of fault impedances).
A broad survey of all analytical applications reveals that they can be categorized into three groups as shown in Fig. 6.1—

1. The first category is targeted towards fast, sub-cycle events like faults, power line disturbances or waveform distortions. The traditional approach for this category has been to use a sensor with a large bandwidth and a fast data acquisition stage that can capture waveforms and upload them to a central server for further analysis.

2. The second category of applications is focused on time horizons ranging from a few minutes to an hour. Examples include analysis of current/power profiles or events like appliances turning on.

3. The last set of applications look at larger time-horizons (hours to days) while extracting meaningful features like power profiles resembling a class of loads (e.g. EVs) or gaining more insights into the consumption behavior of customers. These alerts can be used for planning DER deployments.

Figure 6.1: Categorization of edge-analytics supported by the sensor.
6.2 Sub-Cycle Response to Fast Events

The features examined first are the ones operating at a fast, sub-cycle time interval, representative of the high-speed sampling and data acquisition capability. These features include fault current waveform capture, waveform analytics and spectral decomposition making the sensor ideally suited for monitoring the distribution networks.

6.2.1 Instantaneous Auto-tuning, Fault Identification and Waveform Capture

The PCB-Rogowski coil combined with the DRC integrator has demonstrated the ability to measure currents ranging from 20 mA to over 30 kA, a dynamic range of more than 1 : 1,000,000. As discussed, this lends the unique ability of ‘instantaneous auto-tuning’ for the current sensor to adjust the signal conditioning stage to the current level being monitored.

Previously, the ability of an independently configured current sensor to perform the instantaneous auto-tuning was showcased in Fig. 4.23. In this section, the same concept is shown for the embedded smart sensor developed in Chapter 5.

The sensor mounted on the distribution transformer test setup was subjected to dead-short fault using the circuit shown in Fig. 6.2\(^1\). The cable and transformer impedances were such that the \(\sim 2700\) A\(_{pk}\) fault current could be achieved for 3 cycles.

With the sensor mounted on the transformer, the goal of the experiment was to showcase the ability of the sensor to identify a fault condition, dynamically scale itself and accommodate the full fault waveform through DRC algorithm and initiate a high-speed waveform sampling for the fault waveform. The sensor was successfully able to demonstrate this outcome as shown in Fig. 6.3.

A comparison of the sensor’s performance with the Pearson current sensor is shown in Fig. 6.4. As observed from the blue trace, the waveform can get completely distorted

\(^1\)The primary side (high voltage side) was shorted and the transformer energized through the secondary (low-voltage) side due to the electrical constraints in the lab
6.2.2 In-situ Waveform and Harmonic Analysis

The growing adoption of power electronic loads is causing ever increasing stress on the distribution sub-system infrastructure. Residential loads like LCD TVs, personal computers and more recently electric vehicle (EV) charging stations have significant harmonic
Figure 6.4: Comparison of outputs recorded from Pearson current probe [170] and transformer sensor prototype. The black trace is the current sensor’s voltage output waveform captured on an O’scope, while the red trace is the digitized waveform captured on the sensor.

The assets, particularly service transformers experience the detrimental effects of the non-linear, non-sinusoidal current, leading to increase in heating, losses and damage to internal (winding) insulation. The increasing adoption of these new loads can cause elevated neutral to earth voltages, false ground trips and accelerated degradation of distribution equipment like service transformers, leading to untimely and unforeseen failures [158], [159].

Literature has shown that waveform analysis can offer deeper insights into the degradation of power equipment [48], [62], [63], [95], [152] or even identification of loads [60], [61]. Although these methods are ‘online’ in nature, they rely on real-time data reporting and cloud computing to analyze and identify pre-cursors to catastrophic failures. In this section, advanced capability to store, analyze and identify types of waveforms is built into the sensor, so that it can be programmed to recognize certain types of faults or waveform precursors that are indicative of incipient faults.

In normal operating modes, a high resolution waveform is not particularly useful from a utility operator’s point of view. However, whenever faults or abnormal conditions are detected, the waveform snippets can provide a field operator a much better understanding for
the event, further speeding up the diagnostic or post-event analysis process. For instance, for the 2650 A_{pk} fault, the sensor captured waveform shown in Fig. 6.5 is used to quantify the fault level and store as an alert for the utility operators.

![Figure 6.5: Comparison of (a) Peak current captured on transformer primary (actual corresponding current is 30× lower) and (b) Digitized current captured by the sensor.](image)

Along with fault current waveform captures, the sensor can also capture waveforms which fall outside of the normal operating modes as indicated by waveshapes, harmonic distortion, etc. One way of identifying waveform distortion is to compare the captured waveform with an ideal sinusoid \( x[n] \) and note the severity of the deviations. Let \( i[n] \in \mathbb{I} \) be a data point in the captured current waveform—

\[
i[n] = A \cdot \sin(2\pi n T_s + \phi)
\]  

(6.1)
where $A, \phi$ are the amplitude and phase (unknowns) and $T_s$ the sampling interval. The unknowns can be eliminated by normalizing the captured waveform by $\max\{i[n]\}\forall n$ to get $i'[n]$. The first few elements are used to estimate the phase $\phi$. Subsequently, a point by point comparison with $x[n]$ can reveal whether the captured waveform has any significant deviations worth investigating. An example is shown in Fig. 6.6.

With the wide bandwidth $(20$ Hz to $15$ kHz), the sensor can capture waveforms with significantly higher harmonics as well. Fig. 6.7 shows snippets of a sinusoidal and a triangular current waveform captured and stored on the sensor, which can be subjected to a similar analysis as above. In certain cases, harmonics can provide a better understanding of power disturbance events. Abnormal harmonics are also indicative of asset degradation. For instance in machine fault diagnostics [95], current spectrum of an induction machine can contain abnormal harmonics due to eccentricity faults. Similarly, current harmonics have been reported to cause loss-of-life in distribution and large power transformers [163]. Using the proposed sensor, the current waveform can be analyzed in-situ to extract the frequency spectrum from $0$ to $2$ kHz and raise an alert when abnormal harmonics appear.

Fig. 6.7, shows the harmonic information extracted from the captured sinusoidal and triangular waves. The sensor performed a 512-point Fast-Fourier Transform (FFT) to generate the spectral decomposition of the waveform. The sensor computed FFT (red plot) is
Figure 6.7: FFT computation results for current waveforms that are (a) Sinusoidal (b) Triangular and corresponding captured waveform snippet. Comparison of spectra with MATLAB-based FFT computation of an ideal waveform.

This feature can be used for spectral analysis of other parameters of interest like vibration signatures (for instance, as developed in [184]), acoustics, etc.

While prior work [60], [63] relies on comparing acquired waveforms with data repositories to extract features, the methods result in large data uplinks to the cloud, requiring high speed communication links. Each waveform snippet (16.4 kB) needs to be instantaneously uplinked to the cloud for further analysis, which becomes a challenging task when scaled to millions of devices on the distribution grid. The proposed sensor solves this issue by analyzing data intensive waveforms on the edge of the network, and extracting important
features like distortions or undesirable harmonics to be alerted to the utility. This results in an extremely lean communication network requiring a data exchange as little as a few kilobytes per week, as compared to few megabytes per day of continuous data reporting observed in state of the art.

![Comparison of sensor computed FFT spectra with MATLAB computation for waveforms](image)

**Figure 6.8:** Comparison of sensor computed FFT spectra with MATLAB computation for waveforms that are— (a) Sinusoidal, (b) Square, (c) Triangular (d) Sawtooth.

### 6.2.3 Voltage and Power Quality Alerts

The ability to capture power quality disturbances across the network in a time-stamped manner can offer significant value to utility operators. The sensor has been programmed to detect PQ disturbances like voltage sags, swells and surges. Whenever detected, the sensor triggers a high speed data capture and quantifies the PQ event in terms of magnitude and duration. A few representative experimental results are showcased in Fig. 6.9 and 6.10.

When a severe fault hits a distribution feeder and when several of the sensors capture the varying effects of the same fault, the post-event diagnostic process becomes easier.
Figure 6.9: Sag events captured by the sensor (a) Voltage sag 6 cycle, down to 120 V\textsubscript{rms}, (b) Voltage sag 6 cycle, down to 180 V\textsubscript{rms}.

Figure 6.10: Swell events captured by the sensor 6 cycle, up to 270 V\textsubscript{rms}.
These faults are uplinked to the cloud through available data mules in the form of alerts which are few bytes in size, needing considerably lower bandwidth.

The number of PQ events experienced by an asset in the field, can also impact its overall condition and health. With the embedded edge-intelligence and recorded PQ events, it is possible to create an ITIC curve\(^2\) and send this information to the cloud. For a utility operator, the proposed sensor and GAMMA platform offers a quick snapshot of recorded PQ events across a feeder and help identify areas with severe PQ issues.

6.3 Analyzing Long Time-Horizon Data

In this section, we examine a few edge-computing applications as examples that are suitable for analysis of data acquired over longer time horizons, ranging from a few minutes to days. The focus is not on the actual algorithm, but rather the ability of the sensor to perform complex computations involving large amounts of data and to extract meaningful features hidden in the data that has been captured. This results in an alert being generated for the utility.

The resulting alerts are easier to opportunistically upload to the cloud as high-priority messages (few bytes), rather than uplinking raw data to the cloud for further processing. This method offers distinct advantages over traditional methods. The raw data are locally stored, which can be requested by the utilities at a later time if further inspection is necessary.

6.3.1 Detection of EV Charging Activity

In this section, we show how a load identification algorithm can be implemented on the proposed smart sensor unit.

Load dis-aggregation and Non-intrusive Load Monitoring (NILM) are powerful tools for gathering more insight into types of loads and consumption patterns and eventually

\(^2\)This curve provides an AC voltage boundary that most information technology equipment (e.g. computers) can tolerate or ride through without experiencing unexpected shutdowns or malfunctions
mitigating their impacts on the grid. Several methods have been proposed for detection of different types of loads using power or current profiles [49] - [47], [132]. These methods typically use a sensor to record power consumption or load current periodically and uplink these measurements to the cloud. Cloud-based algorithms process the aggregated data, to determine if the data streams contain certain pre-determined features of interest and then alert the utility operators as necessary. Often times, for cost and complexity considerations, the data are reported to the cloud typically at 15 min intervals, even though the sensor is capable of recording high resolution, high frequency data [48].

A sample application envisioned is to determine if an EV charging station is connected on a service transformer. In this case, the input is a data stream captured over a long time horizon (typically a day to several days) and the output is an identifier or a ‘flag’ indicating if an EV is being charged given the recorded current or power profile. The sensor should analyze the data locally and generate an alert for the utility operator if it detects the pattern of an EV charging cycle. Level 1 EV charging profiles are typically square shaped, more than 3 kW and last for 40 – 45 min or more. Thus, the sensor is programmed to record a 24 hr current profile (at 1 min intervals, 1440 data points), and analyze if it contains a continuous 45 min block with a load of 12 A\textit{rms} or more (thresholds remotely configurable).

Let $i[n] \in \mathbb{R}^{1 \times 1440}$ represent the current measurements. The algorithm can be represented by—

\begin{equation}
\text{Find } i[n], i[n + m], m \geq 45 \text{ such that } i[n + k] \geq 12 \forall k \in [1, 45]
\end{equation}

If an $i[n], i[n + m]$ pair are present, an alert is generated for the utility. Zhang \textit{et al.} [50] have shown a high accuracy, training-free NILM algorithm for detecting EV charging using 1 min AMI data from Pecan Street Data Port [183]. The method fits EV charging profile curves within recorded time-series power data, without ground truth information
Figure 6.11: Aggregated 24 hr current profile for houses #1 − 3 and 7 along with ground truth EV profile, sensor’s estimate compared to [50].

and runs in an offline, MATLAB-based environment on a computer (details can be found in [50]).

To test the edge computing capability of proposed sensor running the ‘rule-based’ engine as shown in 6.2), the same data set was used to analyze 1440 recorded data points corresponding to 1 day worth of data. The sensor can process this data within ~ 500 ms, with a maximum data foot-print of 12 kB, to successfully detect EV charging events,
locally, without cloud intervention and we can see comparable performance levels.

![Figure 6.12: Aggregated 24 hr current profile for house #2 along with ground truth EV profile, sensor’s estimate compared to [50]. It can be seen that a false negative has been recorded using the algorithm in [50].](image)

The sensor’s overall estimation accuracy and mean squared error across all 23 homes recorded in [50] is listed in Table 6.1. Mean squared error is calculated as—

\[
MSE = \frac{||f(t) - g(t)||_2^2}{||g(t)||_2^2} \quad (6.3)
\]

where \(f(t)\) represents the \(1 \times 1440\) sensor estimate vector, \(g(t)\) represents the \(1 \times 1440\) ground truth vector and \(||x||_2\) is the 2—norm of the time-series signal.

Fig. 6.11 is representative comparison of results showing similar accuracy across data from 4 homes. For instance, as seen in Fig. 6.12, the sensor can identify EV charging on house #2 [183], but the NILM algorithm misses out.

Overall accuracy and mean squared error represent the ability to correctly track the
ground truth EV charging waveforms. For instance, as seen in Fig. 6.12, a small error exists in estimating the total current used for EV charging compared to the ground truth. For an accurate NILM algorithm, mean squared error less than 1 is desirable. EV detection accuracy represents the ability to successfully identify if an EV is being charged given a certain consumption profile. It can be seen that the method is highly accurate in raising an initial alert for the utility to further investigate the service configuration for potential EV charging stations.

Table 6.1: EV detection performance comparison from dataset consisting of 23 houses from [183]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Algorithm in [50]</th>
<th>Edge computing on sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>EV detection accuracy</td>
<td>87%</td>
<td>91%</td>
</tr>
<tr>
<td>Mean Squared Error</td>
<td>0.093</td>
<td>0.371</td>
</tr>
<tr>
<td>Overall accuracy</td>
<td>95%</td>
<td>70%</td>
</tr>
<tr>
<td>Computational environment</td>
<td>PC with 64−bit, 2.6 GHz Intel i7 processor running MATLAB</td>
<td>Embedded 32-bit, 48 MHz MSP432 MCU (ARM Cortex M4F)</td>
</tr>
<tr>
<td>Data uplink</td>
<td>~ 12 kB</td>
<td>Less than 200 B</td>
</tr>
</tbody>
</table>

From a system perspective, the proposed sensor and method can eliminate the need for uplinking 12 kB of data to the cloud for further analytics. Through edge-computing, the sensor can effectively ‘compress’ the data into a single alert (few bytes) that represents the presence of EV chargers, which can be uploaded to the cloud using GAMMA platform and data mules. This eliminates the need for expensive, high speed data links, while offering a comparable performance.

6.3.2 Detection of Reverse Power Flows Indicative of Roof Top PVs

The rising adoption of DERs like roof-top (PV) installations are causing voltage issues in distribution networks. Sensors and instrumentation techniques can play a major role in identifying new installations and changes in existing load patterns. Identifying the circuits having high penetration of behind the meter PV installations is the first step to take
corrective actions. At peak insolation, roof-top PV-induced reverse power flows can cause abnormal voltage drops across distribution transformers and significant voltage fluctuations on the distribution feeder. With the proposed sensor, the reverse power flow can be identified and notified to the utilities by analyzing the phase reversal on the captured current waveforms.

![Phase reversal indicative of reverse power flow.](image)

Figure 6.13: Phase reversal indicative of reverse power flow.

For instance, in the prototype pictured in Fig. 5.3, the phase reversal between current and voltage is used to identify potential reverse power injection at the service transformer level. Shown in Fig. 6.13, when the phase difference between the voltage and current sinusoids exceeds $90^\circ$, an alert is generated, indicative of reverse power flow and the presence of PV systems downstream of the sensor. It must be noted that this approach would only work in circuits where reverse injection by roof-top PV inverters is allowed by utilities.

An alternative approach for doing this would be a cloud-based time-series analysis of 15 min interval data reported by a group of smart meters through AMI [132]. The proposed method can drastically reduce the need for uplinking large amounts of data (upto $4 - 10$ kB in 1 day) to just an alert notifying the operators about the presence of reverse power flows, indicative of behind the meter PV installation.
6.4 Impact of Distributed Edge-Intelligence

In this chapter, some examples showcasing integrated analytics through edge-intelligence were demonstrated. The sensor is capable of performing edge-computing activities at varying time-scales, ranging from sub-cycle transient response for capturing faults to analysis of 1000's of datapoints captured over several hours.

By analyzing critical, bandwidth-intensive data at the edge, in a decentralized manner, utility operators can be alerted with important, actionable information pertaining to the health and performance of different assets in the distribution network. Compared to state-of-the-art sensors, the proposed sensor is low-cost and feature-rich, with integrated edge-computing capability capable of operating autonomously without constant cloud communication. Cumulative impact of this approach is low bandwidth requirement for communication, low cloud resources and pre-processed information that reduces the need for deploying customized big-data analytics in the cloud. This can reduce the need for capital intensive deployments of the communication networks as well as the extensive cloud-backend infrastructure that utilities would typically need, with state-of-the-art approaches.
CHAPTER 7
CONCLUSIONS, CONTRIBUTIONS AND RECOMMENDED FUTURE WORK

This dissertation has identified the pressing need for novel smart sensors and architectures for economically monitoring utility assets in the distribution network. Few critical requirements for a viable sensing system include low cost, rapid installation and configuration in the field, ability to sense across a broad operating range and the ability to operate at arbitrary remote locations without cloud connectivity.

A new paradigm of networking with intelligence embedded into the edge of the network for extracting and reporting key features of interest to the utility operators was proposed. The platform, called GAMMA platform, uses long range Bluetooth to communicate with ‘data mules’ to opportunistically connect the last mile connectivity gap. Within this type of architecture, the communication back haul becomes leaner, scalable and inexpensive compared to state of the art approaches.

The functional elements of the platform have been defined, manufactured and experimentally characterized. A functional “smart node” has been developed, acting as a building block for different applications in the distribution asset monitoring space. The design details have been presented and performance has been experimentally validated. The overall feasibility of GAMMA platform has been established through a proof-of-concept application and field trials. GAMMA platform is intended to support a wide variety of applications ranging from power quality monitoring, asset monitoring, smart metering and can be deployed in different settings including urban, semi-urban and rural environments around the world.

A new concept of ‘distributed edge-intelligence’ that forms the basis of advanced, smart sensor solutions has been proposed. This edge-intelligence, each sensor can transform into an edge-computing node and function autonomously. It allows sensors and sensor
networks to be deployed in arbitrary remote locations and to be operated without constant cloud communication. These are important attributes for a distribution grid sensor solution.

Since current sensors are critical for measuring important quantities in the grid, this thesis reviewed state-of-the-art smart current sensor solutions. Some of the key limitations in methods found in literature were identified. A type of low-cost, edge-intelligent “clip-on” current sensor has been developed through this work. The current sensors are based on PCB-embedded Rogowski coils that exhibit good linearity, wide bandwidth, noise immunity and low positional variance. The inherently large dynamic range of Rogowski coils has been further exploited to develop a novel signal conditioning stage that can adaptively compress and unpack waveforms that fall outside of normal operating range. This dissertation has presented the fundamentals of the hardware design, experimental validation and performance characterization for the PCB-embedded Rogowski coil with the adaptive signal conditioning stage. This new method allows designers to develop universal AC current sensors that can measure a wide range of currents and also capture the occasional fault waveform. This has shown major performance improvement over state-of-the-art sensors.

The versatility of the intelligent current sensor technology has seeded the development of advanced transformer monitoring sensors that can be non-intrusively installed on pole-top distribution transformers. The sensor can intelligently record faults and other operational anomalies to be reported to the utility cloud as alerts through the GAMMA platform. The performance of the smart transformer sensor was experimentally demonstrated.

A wide range of possible edge-analytical applications has been demonstrated and discussed in this dissertation. The wide variety covers fast moving events like faults or disturbances to slow moving trends that can be deciphered from days worth of data. This demonstrates the broad extent of computational possibilities on the smart, edge-computing sensor. The ability to extract these meaningful inferences in a low-cost, distributed, decentralized manner can help utility operators gain advanced insights into the operational states of the network.
7.1 Summary of Contributions

In summary, following contributions have been presented through this work—

1. An extensive review of the utility sensor networks, edge computing architectures, smart current sensors and asset monitoring applications for distribution grids has been presented. Critical drawbacks have been identified and a path to implement scalable grid monitoring solutions has been discussed.

2. A unique platform, the GAMMA platform has been developed to enable ‘decentralized and smart’ grid monitoring applications. The platform incorporating intelligence at the grid-edge, relies on a set of trusted partners or data mules to bridge the last mile connectivity gap. An overview of the platform has been presented and key functional elements of the platform have been designed and implemented.

3. Simulation and experimental studies have been done to verify the viability of the platform. A few sample applications that showcase edge computing capability have been designed and implemented within the platform’s framework.

4. A new type of Rogowski coil-based current sensor has been developed using a split-PCB embedded coil. Modeling, analytical and experimental validation of the new “clip-on” sensor has been presented.

5. A unique, adaptive signal conditioning stage for Rogowski coils has been proposed. Detailed analog design has been presented, and verified experimentally.

6. A new algorithm called ‘Dynamic Range Correction’ (DRC) has been developed to instantaneously auto-tune the Rogowski coil-based current sensor to avoid saturation or waveform distortion in the signal conditioning stage. The design details and experimental validation has been presented. With this method, the same sensor can be used to measure currents from 25 mA up to 50 kA.
7. The design of a universal sensor that can be clipped onto conductors for measuring AC currents has been presented. The design and performance of the sensor have been experimentally validated.

8. A low-cost, intelligent sensor to monitor the different parameters of a pole-top distribution transformer has been designed using the intelligent current sensor and GAMMA communication architecture. Key performance metrics have been verified through experiments.

9. A range of edge-computing applications suitable to be deployed on smart sensors for monitoring distribution networks have been discussed and experimentally validated.

A list of different publications and IP generated through this work can be found in Appendix C.
7.2 Recommended Future Work

The future directions for research related to this work can be divided into the following parts—

7.2.1 GAMMA Platform

For making the platform more robust and versatile, few possible research thrusts include—

- The Bluetooth communication range for GAMMA platform is limited by the RF capabilities of the hardware found in common smart phones. Developing a ‘data concentrator’ version of GAMMA Kernel that can act as a relay device between distributed sensors in the field and data mules (smart phones) can significantly boost the communication range of smart phones. This can also enable possibilities of newer Bluetooth or other short range protocol capabilities like BLE mesh.

- Novel strategies for making Bluetooth connections adaptively, through dynamic scanning based on locational information is an important consideration for smart node discovery.

- As the platform evolves and matures, more capabilities can be introduced into the different elements of the platform. A critical capability is to be able to remotely update the smart node firmware through data mules. As different applications keep collecting more and more data, this feature can enable the platform to push better computing and learning models to the edge.
7.2.2 Smart Sensors for Network Management

Few interesting research areas related to smart sensors that could be explored in the future—

- The current sensor developed in this work cannot measure DC currents, as it is based on the Rogowski coil principle. An extension of the work could be to incorporate additional transducers that can measure DC currents (e.g. Hall effect sensors etc.) and a signal conditioning scheme that can account for both the auto-tuning AC current measurement, as well as DC current sensing for accounting for possible offsets or purely DC current measurements.

- Developing ‘application oriented’ smart energy sub-metering devices that can be used for monitoring energy consumption at different points in distribution grids or in indoor environments. For example, a low-cost clip-on sensor developed for building energy monitoring, or metering industrial loads can enable a wide range of data-driven analytical capabilities, along with new revenue models.

- The technology discussed in this work can help in the development of sensors for other utility assets like capacitor banks, reclosers, tie-switches etc.

- Numerous smart sensor applications that can work for emerging markets and for energy access applications can be developed around the GAMMA platform. Low-cost means for achieving distribution automation, decentralized grid stabilization through volt-VAR control, smart account management for energy metering and PAYGO energy access are a few relevant applications that can be explored. An example is explored in Appendix A.

- Developing full load-disaggregation algorithms in an embedded environment, on the sensor can be an interesting research task.
• A field demonstration of the transformer monitoring sensor is planned in the near future. Once deployed on a fleet of pole-top transformers in a utility territory, the sensor can generate interesting data relating to the asset’s actual degradation cycle, which can be leveraged to develop cloud-based (fleet) as well as edge-based (device level) analytical algorithms. The results will help fine-tune the robustness and scalability of the overall sensor platform.
Appendices
Gamma-based Smart Meters and AMI Platform

Gamma platform has been designed to be able to support diverse intelligent applications in smart sensing and automation. Smart energy meters are one of the most widely adopted sensors in the smart grid space around the world. There is a global, growing demand for low-cost, intelligent smart meters that can help utilities gain visibility right up to the network edge and provide some insights into the consumers’ behaviour and their potential impact on grid operations. This demand exists in developed markets like the U.S. and Europe, as well as emerging economies located in South Asia and Sub-Saharan Africa.

Typically, smart meters and AMI networks utilize the hierarchical communication and data aggregation structure like the one shown in Fig. 2.3. This approach is challenged with complexity of deployment, ability to scale rapidly in an economical way and with the ability to operate anywhere in the world.

For broader adoption, the price must be extremely low, with minimal recurring operational and infrastructure costs. While the developed economies are not very price sensitive to the costs of smart meters (in the U.S., smart meters costs from $200 – 300 with additional installation and commissioning), the utilities in emerging economies can be extremely price sensitive. In fact, over a billion people across the world currently live in some form of energy poverty [186] and government agencies and utilities are looking at massive infrastructure projects in bringing smart grid technology to the masses. Smart meters and energy meters that can offer pre-paid ‘pay-as-you-go’ access to electricity can be an effective way of electrifying these communities.

The Gamma platform is ideally suited for addressing these needs. In fact, the genesis of Gamma platform came about from the need for autonomously operating revenue grade smart meters and actuating devices globally.
Figure A.1: Design of a smart meter with pay-as-you-go capability and VAR compensator.

One of the key applications enabled by GAMMA is the deployment of autonomously operating intelligent energy metering nodes. The electrical specifications of the low-cost edge-intelligent energy meter are summarized in Table A.1.

Table A.1: Energy meter specifications

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Form Factor</td>
<td>15 cm × 15 cm × 3 cm</td>
</tr>
<tr>
<td>Electric Network</td>
<td>120 V, 60 Hz or 240 V, 50 Hz</td>
</tr>
<tr>
<td>Input Voltage Tolerance</td>
<td>±20%</td>
</tr>
<tr>
<td>Voltage Resolution</td>
<td>13 mV</td>
</tr>
<tr>
<td>Voltage Accuracy</td>
<td>± 0.5%</td>
</tr>
<tr>
<td>ADC word length</td>
<td>24 bits</td>
</tr>
<tr>
<td>ADC sampling rate</td>
<td>895 kHz with Σ – Δ modulator</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>1.23 kHz</td>
</tr>
<tr>
<td>Phase Resolution</td>
<td>0.02° to 0.024°/LSB</td>
</tr>
<tr>
<td>VAR Support</td>
<td>100 VAR</td>
</tr>
<tr>
<td>Device memory</td>
<td>32 Mbit (6 months+)</td>
</tr>
</tbody>
</table>
These devices are capable of—

- Accurate ($< 1\%$ error) metering of electricity, recording voltage, current, energy, power factor, and frequency in a time-stamped manner. The device is pictured in Fig. A.1.

- The device can record and locally store each data point with a time-stamp at a configurable frequency ranging from $1 – 60$ minutes as per the utility operator’s requirements.

- With integrated GAMMA Kernel (built in), the communication (through data mules), security, cloud infrastructure, data management are all built in through the platform. The setup to verify this functionality is shown in Fig. A.2(a).
• Each device is capable of supporting dynamic pricing and can maintain each individual’s account balance on the device. This can be updated with the cloud asynchronously through data mules as shown in Fig. A.2(c).

• The smart node hosts a relay which can act as a disconnect switch if a user’s account becomes delinquent. For instance, if the user fails to update their account balance (pre-paid money in the account) and the balance runs to zero due to continuous usage, the device can recognize this and cut off power to the user and generate an alert about the same (shown in Fig. A.2(b)).

• The node also hosts a small VAR compensation unit, capable of injecting up to 100 VARs. The unit is activated if the smart node detects prolonged use of poor power factor loads and a sustained dip in the voltage from the configured set point. A fleet of these devices deployed on the distribution feeder can thus dynamically stabilize the voltage profile.

A comparison of the solution with respect to state-of-the-art devices is shown in Table A.2.
Table A.2: Comparison of proposed solution with state-of-the-art

<table>
<thead>
<tr>
<th>Feature</th>
<th>State-of-the-art [187]</th>
<th>Proposed solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>$130 to $200</td>
<td>$30</td>
</tr>
<tr>
<td>Communications</td>
<td>Cellular, Proprietary RF,</td>
<td>BLE 4.2 &amp; mobile phones</td>
</tr>
<tr>
<td></td>
<td>WiFi, Zigbee, Bluetooth,</td>
<td>(data mules)</td>
</tr>
<tr>
<td></td>
<td>Wired</td>
<td></td>
</tr>
<tr>
<td>Data rates</td>
<td>60 kbps to 60 Mbps</td>
<td>~ 1 Mbps</td>
</tr>
<tr>
<td>IT cost</td>
<td>High</td>
<td>Minimal</td>
</tr>
<tr>
<td>Certifications</td>
<td>Required depending on underlying</td>
<td>Minimal, as Bluetooth is globally certified</td>
</tr>
<tr>
<td></td>
<td>technology</td>
<td></td>
</tr>
<tr>
<td>Controls &amp; device</td>
<td>Non-existent/limited</td>
<td>Remote turn-on/off, smart breaker action, VVC, ability</td>
</tr>
<tr>
<td>local intelligence</td>
<td></td>
<td>to support dynamic pricing, markets etc.</td>
</tr>
<tr>
<td>Pay-as-you-go feature</td>
<td>Non-existent/limited</td>
<td>PAYGO capable with remote disconnect on non-payment</td>
</tr>
</tbody>
</table>
To test the EV charging detection algorithm using distributed edge computing, data from Pecan street data port [183] was used. The same data was used for the cloud based method published in [50] and this can serve as a good benchmarking tool for performance comparison. The algorithm in [50] runs on a computer hosting MATLAB in an offline environment, while the proposed method is executed on a 32-bit ARM Cortex M4F MCU (MSP432).

The sensor generated alerts were aggregated and plotted using MATLAB to compare with the results obtained from the alternative method. It can be observed that while the edge-computing method does incur some errors and lower accuracy as compared to the referenced method, the performance levels are comparable and the edge-computing approach can have significantly lower infrastructure requirement. Each smart sensor can analyze the data locally and generate an initial alert for the utility in order to examine the service configuration.

The findings have been summarized below—
Figure B.1: Sensor-based edge computing outcome for homes #1 – #12
Figure B.2: Sensor-based edge computing outcome for homes #13 – #23
APPENDIX C

PUBLICATIONS AND INTELLECTUAL PROPERTY GENERATED THROUGH THIS WORK

C.1 Journal Publications


C.2 Conference Papers and Presentations


### C.3 Patent Filings


REFERENCES

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VITA

Shreyas Kulkarni was born on January 19\textsuperscript{th}, 1993 in Mumbai, India. His family moved to the nearby city of Nashik, where he completed his schooling. Since a young age he took a keen liking towards Science and Mathematics, winning several prestigious regional and national scholarships. He joined College of Engineering, Pune where he completed the B.Tech degree in Electronics & Telecommunication Engineering in 2014. While at COEP, he was part of the Student Satellite project, “Swayam”, where he designed the power system and the on-board computer hardware. He led the team and was system engineer for the project from 2013 to 2014. During 2015, he was at IIT Bombay—Applied Power Electronics Lab as a research associate. In 2015, he was admitted to Georgia Tech for the Ph.D. program under the guidance of Prof. Deepak Divan at the Center for Distributed Energy. During graduate school, he worked on several projects related to smart sensors for the power grid. He earned the M.S. in Electrical & Computer Engineering from Georgia Tech in 2017. He has a keen interest in electronics, aerospace systems and hardware design. He has served as a peer-reviewer for numerous academic journals and conferences. In his free time, he is an avid foodie who enjoys the outdoors, likes collecting rare coins, playing chess, swimming and hiking.