# An Architecture for Intelligent Data Processing on IoT Edge Devices

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*Abstract*— **As the Internet of Things edges closer to mainstream adoption, with it comes an exponential rise in data transmission across the current Internet architecture. Capturing and analyzing this data will lead to a wealth of opportunities. However, this ungoverned, unstructured data has the potential to exhaust the resources of an already strained infrastructure. Analyzing data as close to the sources as possible would greatly enhance the success of the IoT. This paper proposes a distributed data processing architecture for edge devices in an IoT environment. Our approach focuses on a vehicular trucking use case. The goal is to recreate the traditionally centralized Storm processes on the edge devices using a combination of Apache MiNiFi and the user's custom-built programs. Our approach is shown to preserve computational accuracy while reducing by upwards of 90 percent the volume of data transferred from edge devices for centralized processing.**

***Keywords: Internet of Things, Context Aware Computing, Edge Processing, Apache Nifi, Apache MiNiFi, Data Distribution***

## I. INTRODUCTION

The "Internet of Things" is a paradigm in which objects such as household appliances, automobiles and even humans will be assigned IP addresses. Such connectivity requires new research methods and solutions to address issues surrounding the imminent overflow of data. With 28 billion connected devices predicted by 2021 [1], data processing and filtering on the edge is becoming a priority for many of the world's leading technology companies.

Traditionally, enterprises have stored large volumes of unfiltered data in data centres. Such centralized data storage limits organizations as they are unable to capitalize on timely insights. More recently, leading technological companies have focused on building analytics solutions that can derive value from data in motion, otherwise known as real-time processing. Real-time processing occurs with close to zero latency, giving businesses instant access to urgent business situations that can only be detected and acted on at a moment's notice, also known as perishable insights [2].

This paper proposes a distributed data processing architecture for edge devices in an IoT environment. Our architecture proposes a data filtering algorithm and utilizes the Hortonworks Data Flow (HDF) analytics platform and Apache Minifi. We evaluate a vehicular trucking scenario using a standardized data set [13].

Our evaluation considers driver performance consisting of average speeds and unsafe event notifications. Our work enriches the data produced for Apache Spark ML prediction model. We implement data filtering to capture perishable insights on the edge devices. Our architecture, which contextualizes data close to the edge, is compared against the standard mechanism in which data is centrally processed. Our approach is shown to preserve computational accuracy while reducing by up to 90% the volume of data transferred from edge devices.

This paper is organized as follows. Section II discusses relevant related work. An overview of candidate technologies is presented in Section III. Section IV initially presents the existing HDF analytics platform. It then discusses the enhancements proposed through this work. Results are presented in Section IV. Finally, conclusions and future work are described in Section V.

## II. RELATED WORK

[3] proposes a platform called IFoT (Information Flow of Things). IFoT performs distributed processing, distribution and analysis of data streams near the source based on a "Process On Our Own (PO3)" concept. [4] designs a real-time job scheduler in Hadoop for Big Data processing. The case study is applied as support for Smart City applications, cabs in particular. The scheduler aims to manage cluster resources in such a way that the real time jobs will not be affected by the long running batch jobs or vice-versa. However, all data is sent to the centralized scheduler for processing.

A NECtar Agent, a solution that automates the switching between different data handling algorithms at the network edge is proposed in [5]. The aim is to provide a solution for network-edge data reduction and achieves accuracies between 76.1 % and 93.8 % despite forwarding only 1/3 of the data items. However, certain scenarios would require a higher accuracy than NECtar could provide. [6] proposes a Big Data pre-processing quality framework that focuses on the Quality of Big Data (QBD). This framework aims at solving data quality issues that occur when attempting to apply data quality concepts to large data sets. However, the pre-processing does not occur on the edge devices. [7] is an open-source solution initiated by Cisco, but has been acquired by Eclipse. Krikkit is a publish/subscribe mechanism where rules are registered on edge gateways that have visibility into and communicate with sensors. It is in the process of specifying a data format and a mechanism for "telling the network-edge devices" which data to forward and how.

## III. TECHNOLOGY OVERVIEW

This section provides an overview of technologies and methods used in this paper.

For this work, Hortonworks Data Flow (HDF) was used to analyze real time data processing. HDF [8] is a suite of tools that give the user full control of data from its generation on the edge devices, while solving the real time challenges of collecting multiple types of data from a multitude of sources. There are three main tools within HDF; Apache NiFi, Apache Kafka and Apache Storm.

*Apache NiFi* is primarily a data in motion technology that uses flow based processing. NiFi [9] provides a GUI and contains over 200 processors. Each processor performs an action on the passing data. The user can drag and drop processors onto the canvas, adjust the configurations in each processor before connecting it to the following processor, creating a real time dataflow.

The built in NiFi processors can perform a multitude of actions such as convert data formats, add attributes to the data, and route the data based on attributes. There is also a collection of processors available for ingesting data from a multitude of sources including websites, local file systems, databases, and external sources such as edge devices. Created by the National Security Agency (NSA), NiFi addresses many of the technical challenges associated with IoT. NiFi adds extra security to the transportation of data with built-in support for SSL, SSH, HTTPS, encrypted content and role-based authentication/authorization and handles a diversity of datatypes as described above [9]

*Apache Kafka* [10] will be used as the messaging service as it provides high throughput, reliable delivery, and horizontal scalability. Kafka is a low latency-messaging platform for real-time streaming data sources. Within Kafka, there are four main components; Producers, Consumers, Topics and Brokers. Kafka messages are organized into Topics, which are a category or feed name to which records are published. A producer pushes messages to a specific topic; a consumer pulls messages from a specific topic. Kafka runs in a cluster, as it is a distributed system, and each node in the cluster is known as a broker.

*Apache Storm* [11] is a distributed computation system that performs real time processing on large amounts of data. There are five key elements of Storm; Tuples, Streams, Spouts, Bolts and Topologies. A Tuple is a list of ordered elements. Generally, it is a set of comma-separated values. A stream is an unbounded sequence of tuples that is processed and created in parallel in a distributed fashion. Spouts are the source of data; in this case, they will be the Kafka Topics. Bolts are the process units. They process incoming streams and produce output streams. Topologies can be viewed as a network of spouts and bolts.

*Apache Spark MLlib* (Machine Learning) [12], although not part of HDF, can be used to build prediction models using historical data. Prediction models can also make use of "enriched" data, where data from the edge device is enriched with publicly available contextual data such as weather data. Figure 2 illustrates how the data is enriched before being transformed for Spark ML. Storm makes predictions by feeding the incoming events to the prediction model in real time.

## IV. ARCHITECTURAL IMPLEMENTATIONS

We evaluate a vehicular trucking scenario in which the HDF analytics platform and Apache Minifi are used. A streaming analytics use case for a fleet of trucks as specified in [13] is considered. In the HDF application, a data simulator creates the data. Table 1 illustrates an example of data created. Trucks generate millions of events for any given route. Normal events include vehicle starting, vehicle stopping etc. Violation events include speeding, excessive acceleration, excessive breaking and unsafe tail distance. The HDF analytics platform streams these events to Storm. Storm filters violations and performs real-time analysis, detecting erratic behavior for a driver over a short period. If a driver creates five violations in a three-minute window, an alert is sent directly to the fleet manager.

Spark MLlib is implemented to transform HDF from a streaming application to a prediction application on future driver violations.

In the HDF use case, NiFi ingests all data from the edge devices and separates the data into two dataflows. In figure 1, the first dataflow, "truck_geo_events", extracts the lines of data featuring the truck events. The second dataflow, "truck_speed_events", extracts the lines of data featuring the speed of the truck. These dataflows are passed to Kafka Topics and to Storm Spouts. Storm bolts perform the real time computations. Results can be viewed in real time through a GUI.

Our evaluation consists of two architectural implementations. Implementation 1 builds on the traditional centralized processing approach. MiNiFi is used on the edge devices to perform simple processing and filtering before forwarding data to the main NiFi server for further data enrichment. Implementation 2 evaluates our enhanced architecture in which processing, filtering and data enrichment occur on the edge devices. Our enhanced architectures contextualize data close to the edge thereby reducing network load.

### *A. Architectural Implementation 1 - Centralised Data Processing*

Minifi, a sub project of Nifi, was installed on Raspberry Pis representing edge devices. Fig 3 shows the dataflows created on the edge device through MiNiFi. Dataflow 1 calculates the average speed. Dataflow 2 filters unsafe events. Dataflow 3 determines if five unsafe events have occurred within three minutes. If true, an email is sent directly to the fleet manager. All data is saved locally which can be uploaded in batch at a later stage. The main Nifi server ingests the data from the edge devices for further processing.

Table 1: Original data Created by Simulator

| Time | Data | TruckID | DriverID | Driver | RouteID | Route | Event | Lat | Lon | Speed |
|---|---|---|---|---|---|---|---|---|---|---|
| 13:50 | Truck_geo_event | 29 | 10 | George Vetticaden | 1390372503 | St.Louis to Tulsa | Unsafe Tail Distance | 36.37 | 95.18 | -------- |
| 13:52 | Truck_speed_event | 83 | 13 | Suresh Srinivas | 1556150946 | Des Moines to Chicago | ------------ | ------ | -------- | 68 |

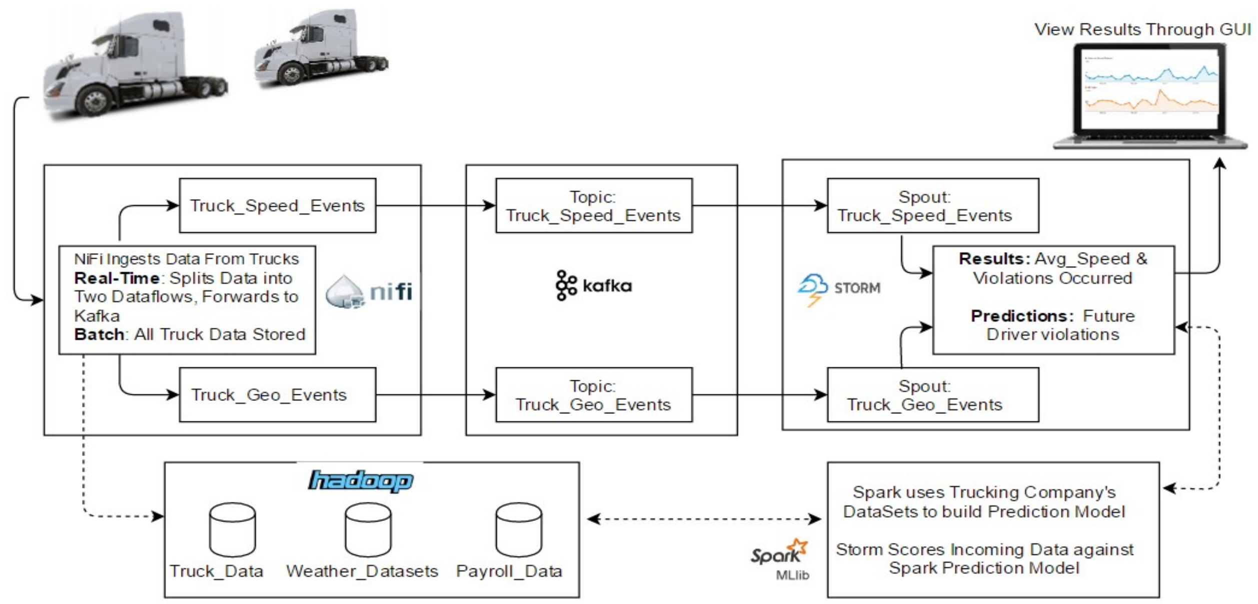
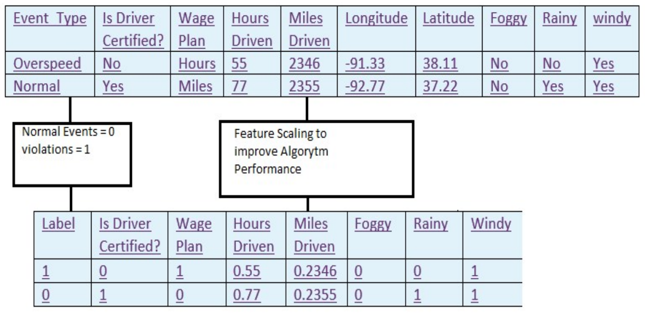

View Results Through GUI
NiFi Ingests Data From Trucks
Real-Time: Splits Data into Two Dataflows, Forwards to Kafka
Batch: All Truck Data Stored
nifi
Truck_Speed_Events
Truck_Geo_Events
Topic: Truck_Speed_Events
kafka
Topic: Truck_Geo_Events
STORM
Spout: Truck_Speed_Events
Results: Avg_Speed & Violations Occurred
Predictions: Future Driver violations
Spout: Truck_Geo_Events
hadoop
Truck_Data
Weather_Datasets
Payroll_Data
Spark MLlib
Spark uses Trucking Company's DataSets to build Prediction Model
Storm Scores Incoming Data against Spark Prediction Model

Figure 1: HDF Architecture with NiFi and Kafka Feeding Data into Storm Bolts for Processing. Apache Spark Creates Prediction Model



| Event Type | Is Driver Certified? | Wage Plan | Hours Driven | Miles Driven | Longitude | Latitude | Foggy | Rainy | windy |
|---|---|---|---|---|---|---|---|---|---|
| Overspeed | No | Hours | 55 | 2346 | -91.33 | 38.11 | No | No | Yes |
| Normal | Yes | Miles | 77 | 2355 | -92.77 | 37.22 | No | Yes | Yes |

Normal Events = 0
violations = 1
Feature Scaling to improve Algorytm Performance

| Label | Is Driver Certified? | Wage Plan | Hours Driven | Miles Driven | Foggy | Rainy | Windy |
|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 0.55 | 0.2346 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0.77 | 0.2355 | 0 | 1 | 1 |

Figure 2: Transforming Data to Spark ML Prediction Model Format

To separate the incoming sensor data into individual dataflows, a RouteText processor is configured with regular expressions that forward truck_speed_events and truck_geo_events to separate dataflows. Truck_geo_events is subsequently split into two dataflows.

The Speed_events data, (dataflow 1), consists of a MergeContent processor that merges single flowfiles into a user specified amount. This is useful when performing computations that require a specified timeframe of data or a certain amount of data. A following processor, UpdateAttribute gives the merged content a filename. Once the content is merged into a file, the ExecuteStreamCommand processor is configured to run the users pre-built program in real time. The outcome of this dataflow will provide an average speed over five seconds. Once the processing has been completed , the results can be stored locally or forwarded to the main NiFi server. This system can be altered for different scenarios and can perform more complex computations with different programs through the ExecuteStreamCommand.

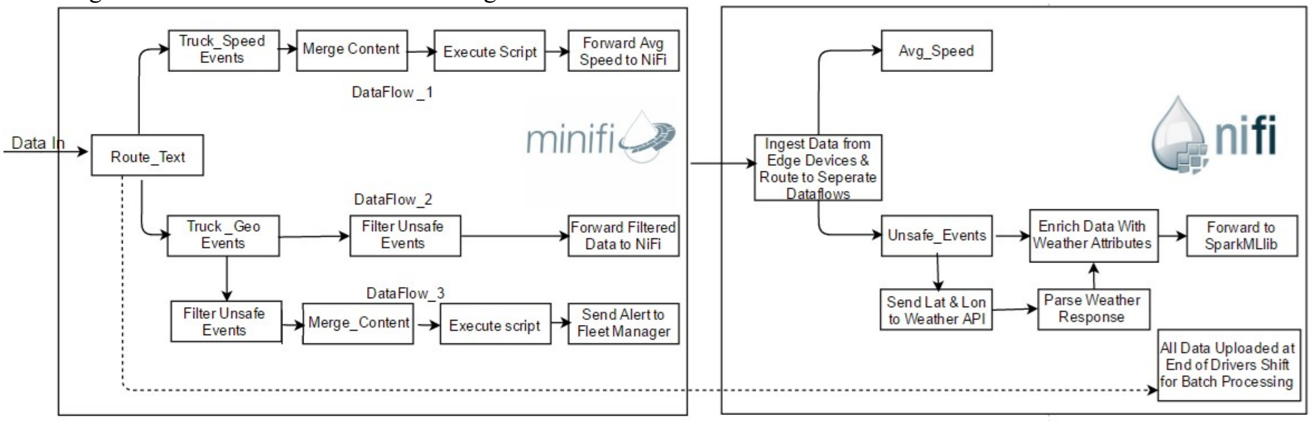
Dataflow 2 uses a RouteText processor to filter out all “unsafe” events, which are then forwarded to the main NiFi server.

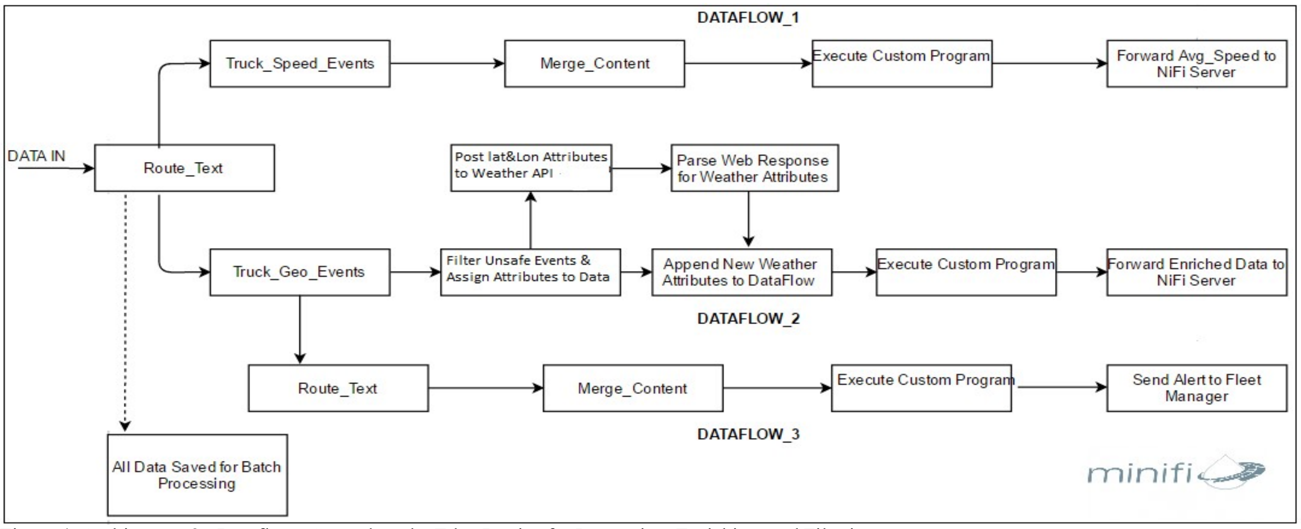
In the HDF use case, Storm sends an alert to the fleet manager whenever a driver creates five unsafe events in a three-minute time window. Dataflow 3 emulates this action using a RouteText processor to filter out unsafe events. This data is merged into a file containing three-minutes of data. A custom program calculates if five violations have occurred in that time. If true, a PutEmail processor will alert the fleet manager immediately with a file containing a list of violations occurred.

The Nifi server ingests and separates incoming data from the edge devices. The average speed data is extracted and can be forwarded to a dashboard for further analyzing, or forwarded to storage. Unsafe events are also extracted. A dataflow is created on the main NiFi server to enrich all unsafe events with real-time weather attributes. This dataflow consists of a number of processors that split the data into attributes, send the latitude and longitude attributes to a weather API using an InvokeHTTP processor and receives an immediate weather response in JSON format. An EvaluateJSONpath processor parses the JSON file for weather in relation to wind, rain and fog. These new weather attributes are then appended to the original Geo_events flowfile. A conversion is executed on the incoming data to translate attributes including weather and events into binary, preparing it for the Spark prediction model.

*B. Architectural Implementation 2 - Edge Data Processing*

In this section we describe our architectural implementation where processing, filtering and data enrichment occur on the edge devices. Figure 4 illustrates the three dataflows created on the edge device for this scenario. Dataflow 1 calculates the average speed. Dataflow 2 enriches each unsafe event with weather attributes, and prepares it for the SparkML prediction model. Dataflow 3 is identical to dataflow 3 in scenario 1.


Data In
Route_Text
Truck_Speed Events
Merge Content
Execute Script
Forward Avg Speed to NiFi
DataFlow_1
minifi
DataFlow_2
Truck_Geo Events
Filter Unsafe Events
Forward Filtered Data to NiFi
DataFlow_3
Filter Unsafe Events
Merge_Content
Execute script
Send Alert to Fleet Manager
Avg_Speed
Ingest Data from Edge Devices & Route to Seperate Dataflows
nifi
Unsafe_Events
Enrich Data With Weather Attributes
Forward to SparkMLlib
Send Lat & Lon to Weather API
Parse Weather Response
All Data Uploaded at End of Drivers Shift for Batch Processing
Figure 3: Architecture 1 - Dataflows on Minifi Edge Device. Nifi Server Ingests Data from Edge Devices


DATAFLOW_1
Truck_Speed_Events
Merge_Content
Execute Custom Program
Forward Avg_Speed to NiFi Server
DATA IN
Route_Text
Post lat&Lon Attributes to Weather API
Parse Web Response for Weather Attributes
Truck_Geo_Events
Filter Unsafe Events & Assign Attributes to Data
Append New Weather Attributes to DataFlow
Execute Custom Program
Forward Enriched Data to NiFi Server
DATAFLOW_2
Route_Text
Merge_Content
Execute Custom Program
Send Alert to Fleet Manager
DATAFLOW_3
All Data Saved for Batch Processing
minifi
Figure 4: Architecture 2 - Dataflows Created on the Edge Device for Processing, Enriching, and Filtering

## VI.RESULTS

This section outlines the results of the evaluation of the architectural implementations described in the previous section. The evaluation is undertaken with and without weather context. The simulation is configured to create data for both one driver and 23 drivers. The quantity of data produced is controlled by increasing the granularity of data production from 500ms, 250ms to 100ms.

## A. *Evaluating the Quantity of Data Transmitted Without Weather Context*

In this section we compare the performance of architectural Implementation 1, which uses a traditional centralized processing approach and architectural implementation 2 in which processing, filtering and data enrichment occur on the edge devices. Evaluations are undertaken without weather context. Table 2 illustrates the quantity of data transmitted from the edge device in the single driver evaluation.

| Data Intervals (ms) | Central Processing Data Transmitted (KB) | Edge Device Processing Data Transmitted (KB) | Data Reduction |
|---|---|---|---|
| **100** | 625.76 KB | 10.43 KB | 98.33% |
| **250** | 297.82 KB | 8.72 KB | 97.07% |
| **500** | 141.48 KB | 8.66 KB | 93.88% |

Table 2: Quantity of Data Transmitted – Single Driver (Without Weather Context)

Figure 5 graphically represents the data from Table 2. It illustrates that our enhanced architectural implementation reduces the quantity of data required to be transmitted for centralized processing by up to 98%.

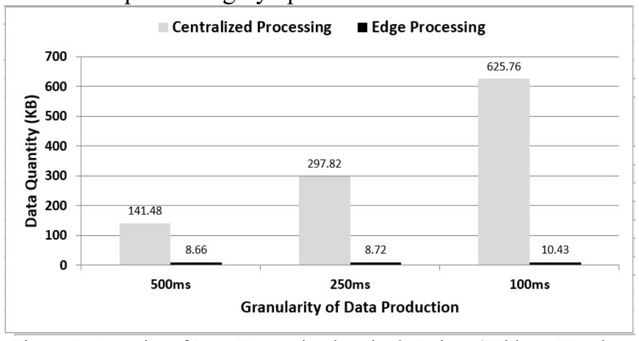


Figure 5: Quantity of Data Transmitted – Single Driver (Without Weather Context)

Table 3 illustrates the quantity of data transmitted from the edge device for a 23 driver evaluation when the effect of weather was not considered.

| Data Intervals (ms) | Central Processing Data Transmitted (KB) | Edge Device Processing Data Transmitted (KB) | Data Reduction |
|---|---|---|---|
| **100** | 13420 | 344.7 | 97.43% |
| **250** | 6140 | 162.66 | 97.35% |
| **500** | 3240 | 88.95 | 97.25% |

Table 3: Quantity of Data Transmitted – 23 Drivers (Without Weather Context)

Figure 6 graphically represents the data from Table 3. It illustrates that our enhanced architectural implementation reduces the quantity of data required to be transmitted for centralized processing by up to 98%.

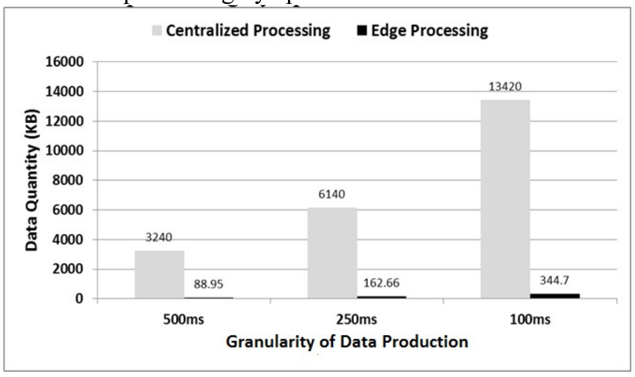


Figure 6: Quantity of Data Transmitted – 23 Drivers (Without Weather Context)

Tables 2 and 3 illustrate that from both a single driver and 23 drivers evaluation, as the velocity of data increased a slight increase in performance was experienced. In the single driver scenario there was a 93.88% reduction in data transmitted when data was processed on the edge device at 500ms granularity. When the data production rate was increased by a factor of 5 with data produced every 100ms the data reduction by processing on the edge device increased to 98.33%. The improved performance results from merged content when calculating the average speed. When data was created at higher velocity, more content needed to be merged to aggregate 5 seconds of data, yet still resulting in one output.

## B. *Evaluating the Quantity of Data Transmitted With Weather Context*

In this section we compare the performance of centralized processing and edge processing considering the effect of weather conditions. Table 4 illustrates the quantity of data transmitted from the edge device in the single driver evaluation with weather context.

| Data Intervals (ms) | Central Processing Data Transmitted (KB) | Edge Device Processing Data Transmitted (KB) | Data Reduction |
|---|---|---|---|
| **100** | 626.43 | 37.97 | 93.94% |
| **250** | 288.57 | 27.18 | 90.58% |
| **500** | 144.58 | 17.22 | 88.09% |

Table 4: Quantity of Data Transmitted – 1 Driver (With Weather Context)

Figure 7 graphically represents the data from Table 4. It illustrates that our enhanced architectural implementation reduces the quantity of data required to be transmitted for centralized processing by up to 94% when the context of weather conditions is considered.

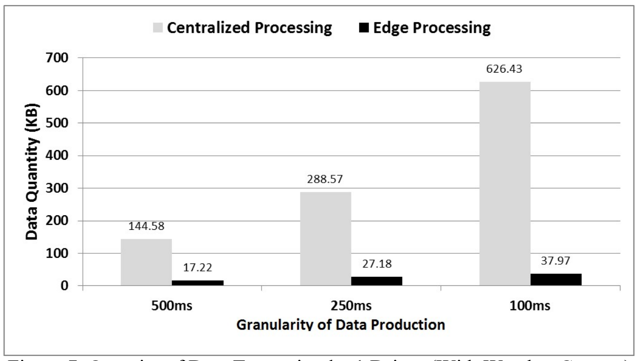


Figure 7: Quantity of Data Transmitted – 1 Driver (With Weather Context)

Table 5 illustrates the quantity of data transmitted from the edge device for a 23 driver evaluation when the effect of weather was considered.

| Data Intervals (ms) | Central Processing Data Transmitted (KB) | Edge Device Processing Data Transmitted (KB) | Data Reduction |
|---|---|---|---|
| **100** | 13430 | 2659.6 | 80.2% |
| **250** | 6140 | 1153.66 | 81.21% |
| **500** | 3230 | 620.26 | 80.8% |

Table 5: Quantity of Data Transmitted – 23 Drivers (With Weather Context)

Figure 8 graphically represents the data in Table 5.

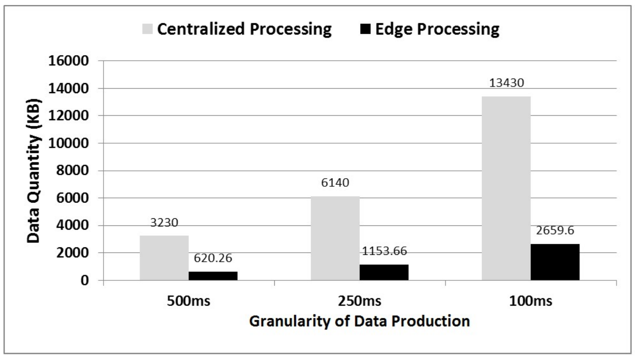


Figure 8: Quantity of Data Transmitted – 23 Drivers (With Weather Context)

Tables 4 and 5 illustrate that when the context of weather is included our edge processing approach still has good performance in comparison to a centralized processing approach when considering data transmission and computational accuracy. The results do however illustrate that when weather context is considered, dangerous drivers create more unsafe events. These unsafe events generate multiple weather requests which are processed on the edge device. In the single driver scenario, the driver was considered "safe". The results for this individual safe driver have up to a 94% data transmission reduction, even when weather context is considered.

## V. CONCLUSION

This work creates an enhanced distributed data processing architecture for edge devices in an IoT environment. The approach reduces significantly the need for centralized data processing while preserving computational accuracy. We evaluate a vehicular trucking scenario using a standardized data set. The evaluation is undertaken with and without weather context. The simulation is configured to create data for both one driver and 23 drivers. The quantity of data produced is controlled by increasing the granularity of data production. Results presented illustrate that our enhanced architecture reduces data transmission by up to 98%. Our results do however illustrate that when weather context is considered, dangerous drivers create numerous unsafe events. These unsafe events generate multiple weather requests which are processed locally thereby slightly reducing data transmission performance.

Future work combining MiNiFi, NiFi and Apache SparkMLlib will enable us to utilize machine-learning mechanisms as the data is created.

## REFERENCES

[1] Ericsson, "Cellular networks for massive IoT," Ericsson, 2016.

[2] Gualtieri, M; Curran,R, "The Forrester Wave™: Big Data Streaming Analytics, Q1 2016," Forrestor.com, Cambridge MA, 2016.

[3] Y. Nakamura, H. Suwa, Y. Arakawa, H. Yamaguchi and K. Yasumoto, "Middleware for Proximity Distributed Real-Time Processing of IoT Data Flows," 2016 IEEE 36th International Conference on Distributed Computing Systems (ICDCS), Nara, 2016, pp. 771-772

[4] C. Barbieru and F. Pop, "Soft Real-Time Hadoop Scheduler for Big Data Processing in Smart Cities," 2016 IEEE 30th International Conference on Advanced Information Networking and Applications (AINA), Crans-Montana, 2016, pp. 863-870

[5] A. Papageorgiou, B. Cheng and E. Kovacs, "Real-time data reduction at the network edge of Internet-of-Things systems," 2015 11th International Conference on Network and Service Management (CNSM), Barcelona, 2015, pp. 284-291

[6] I. Taleb, R. Dssouli and M. A. Serhani, "Big Data Pre-processing: A Quality Framework," *2015 IEEE International Congress on Big Data*, New York, NY, 2015, pp. 191-198.

[7] "eclipse.org/krikkit/," Eclipse, [Online]. Available: https://eclipse.org/krikkit/. [Accessed 03 February 2017].

[8] "HortonWorks DataFlow," Hortonworks, 2016.

[9] 451 Research , "Everything Flows: The value of stream processing and streaming integration," 451 Research, 2016.

[10] HTC Global Services, "Apache Kafka – Your Event Stream Processing Solution," htcinc.com.

[11] R. Evans, "Apache Storm, a Hands on Tutorial," 2015 IEEE International Conference on Cloud Engineering, Tempe, AZ, 2015, pp. 2-2

[12] Meng et al, "MLlib: Machine Learning in Apache Spark," Journal of Machine Learning Research 17, San francisco, 2016.

[13] G. Vetticaden, "github.com/georgevetticaden/hdp," 10 December 2016. [Online]. Available: https://github.com/georgevetticaden/hdp/tree/master/reference-apps/iot-trucking-app.