Multivariate Interpolation at the Edge to Infer Faulty IoT Sensor Metrics

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Abstract: Virtual sensors are software entities that allow the estimation, through models, of critical variables in a given environment. Metrics can be modeled computationally to estimate the values measured by a sensor without installing it physically in the specified location. The monitoring and control of its variables by the edge are of great importance, as they are directly related to increased productivity. This article presents the idea behind virtual sensors, discusses some challenges and trends, presents such sensors' modeling for estimating values, and gives results based on a Smart Farming case study. The results show that the virtual sensors' estimated values are very close to reality, which shows that our method can be used with very high confidence.

1 INTRODUCTION

Edge Computing (Mahmoudi et al., 2018) is a paradigm that complements the Cloud Computing model, aiming to process data on servers close to users, that is, close to where data is generated and consumed. In this way, data travels shorter distances, which dramatically reduces latency to a few milliseconds. For this reason, Edge Computing is a crucial factor in the consumption of data coming from the Internet of Things (IoT). More and more sensors, cameras, and systems will monitor the entire industrial production process, evaluating and supervising the equipment's performance. All of this has as main objectives: saving resources, decreasing the average time spent on production, and raising the quality of products. Sensors may measure position, temperature, pressure, and other physical or chemical parameters. A sensor is a technical component that converts physical or chemical quantities in an electrical signal. However, there are cases where the desired physical amount cannot be measured directly through a physical sensor due to cost, energy, convenience, failure, or other practical reasons, such as geography or space. Based on these specific contexts, virtual sensors appear as a viable option.

This article introduces a new approach to estimate values of a virtual position (so-called virtual sensor) based on values collected from real sensors within the same region. Our contributions can be summarized as follows: (i) a multivariate interpolation model for estimating values at positions addressed by virtual sensors; (ii) a simulation for estimating the values assigned to virtual sensors, considering the physical sensors distributed in the environment; (iii) an algorithmic implementation that allows using the proposed mathematical model in real environments; and (iv) evaluations of the proposed model against well-known techniques in the literature, demonstrating the advantages of the model presented in this article. Op-

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timizing the farms' production process is the main reason for applying IoT to the production line. It allows today's equipment that makes up the farms' industrial yard to be connected in a network. It means that it makes all industrial machinery work automatically using highly programmable intelligent sensors. The main difference to the current scenario, which is already packed with modern equipment, is that people control these machines. With Smart Farms, the market can expect in a few years that these machines will be independent and interact with each other and with the general farm system. It means that the equipment will make decisions without human intervention.

2 VIRTUAL SENSORS

The virtual sensor is not a physical sensor but behaves as such. Virtual sensors are software-driven models that use available information from other measurements and parameters to calculate an estimate of the metric of interest, approximating the behavior of a physical sensor. A virtual sensor can be created as a function of other real physical sensors, and there must be a correlation between the inputs and the virtual sensor. A virtual sensor can simulate and replace a real physical sensor through modeling that estimates output values with the same reliability as a real sensor. These sensors can act as a backup, where the use of a physical sensor is made impossible by several factors such as remote geographic location or sensor failure (Liu et al., 2009).

Virtual sensor modeling can be based on empirical data, where historical data is used to derive a correlation between outputs and inputs. It can be found in analytics, which uses physical formulas for modeling. The models proposed in the literature indicate two ways virtual sensors provide values: analytical and empirical models. In analytical models, the virtual sensor calculates metrics based on physical laws. In contrast, in empirical models experience is incorporated into the calculus (Liu et al., 2009). The definition of the modeling technique depends on the sensor design, application, and mathematical calculation approach. Another goal of using virtual sensors is to replace a physical sensor and its functions. In this type of application, the main objective is to replace a real sensor in case of failures or the impossibility of installing a physical sensor on site. The related work reveals that the application areas of virtual sensors are quite different. We chose to classify applications into large areas to facilitate visualization in this work.

- **Industry:** Virtual sensors are modeled to produce new measurement data in order to improve production processes (Shao et al., 2018). In (Tong and Zewen, 2017) virtual sensors are created to estimate measurements in places where it is not possible to use a real sensor, for example, measuring the performance of machines or measuring chemical processes in oil extraction.
- **Environment:** Wang, Zhao, and Cui (Wang et al., 2015) describe the use of virtual sensors to monitor algal blooms. In (Asy'ari et al., 2019) virtual sensors are used to measure solar radiation.
- **Health:** Erturk and Vollero (Erturk and Vollero, 2020) developed virtual sensors to improve surgical accuracy. In (Gupta and Mukherjee, 2016) virtual sensors are used to monitor and predict hemorrhages in remote patients.
- **Agriculture** Sánchez-Molina (et al.) (Sánchez-Molina et al., 2015) developed a virtual sensor applied to monitoring the amount of water in the biomass of the tomato crop. Moura (et al.) (Zhang et al., 2020) uses virtualized sensors to provide different measures of soil irrigation based on statistical data.
- **Sensors-as-a-Service:** This category appears as a new trend in IoT. It creates virtual sensors to make data from physical sensors available in the cloud. In this way, different applications can use data from these virtual sensors for their solutions without the developer having access to the physical sensor (Fanti et al., 2018) (Ilyas et al., 2020) (Flores et al., 2018).

Different virtual sensor modeling techniques are presented in the literature. In this work, the modeling techniques were divided into large areas to facilitate work classification as shown in Table 1.

Table 1: Virtual sensor modeling techniques.

Technique	Article
Machine Learning Models	(Wang et al., 2015) (Asy'ari et al., 2019) (Yuan et al., 2020) (Ilyas et al., 2020) (Zhang et al., 2020)
Mathematical Models	(Cristaldi et al., 2020) (Tong and Zewen, 2017) (Fanti et al., 2018) (Shao et al., 2018) (Sutarya and Mahendra, 2015)
Generic Models	(Sánchez-Molina et al., 2015) (Gupta and Mukherjee, 2016) (Flores et al., 2018) (Erturk and Vollero, 2020)

Virtual sensor modeling applied in the industry uses machine learning techniques or mathematical models. Virtual sensors applied in Health and Agriculture mostly use modeling techniques based on generic models. Finally, Sensor-as-a-Service is modeled using different types of modeling techniques. Therefore, more and more virtual sensors are being implemented in various applications, and multiple methods are used to model these sensors. However, it is still a challenge to determine which modeling technique is the most suitable according to the type of application, considering the types and amount of input data of the models, the response time, and the computational resources needed for the modeling.

3 PROPOSED METHOD

The initial resource for a refined development of the numerical method is strongly associated with the dependence on the location of the plotted mesh nodes with a minimum number of elements. In this sense, our proposal focus on discretizing the domain of a simple geometric mesh in 2D through triangulation. Therefore, we use concepts from the geometry of triangles. For this, consider $A = (x_A, y_A)$, $B = (x_B, y_B)$ and $C = (x_C, y_C)$ the Cartesian coordinates of three points of a plane where the area with the sign of a triangle (S_{ABC}) is given by:

$$S_{ABC} = \frac{1}{2} det \begin{pmatrix} x_A & y_A & 1 \\ x_B & y_B & 1 \\ x_C & y_C & 1 \end{pmatrix}. \quad (1)$$

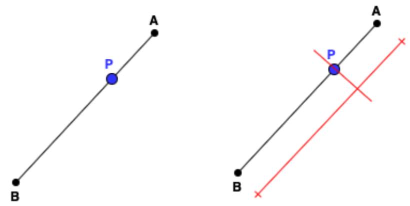
If the area of the triangle is null ($S_{ABC} = 0$), then the points A, B, and C are collinear (may be coincident). This collinearity of the points is defined as a degenerated triangle and otherwise a non-degenerated triangle. Additionally, if A, B and C are arranged counterclockwise, we have $S_{ABC} = +\nabla ABC$ and clockwise, $S_{ABC} = -\nabla ABC$, where ∇ABC is the conventional area of a triangle ΔABC. This definition introduces the decomposition property for the signed area; that is, given a point P in the plane, there are three other sub-triangles (ΔPBC, ΔPCA, and ΔPAB). Note that the sum of the areas of these sub-triangles is equal to the area of ΔABC. From there, it is possible to define whether the point P is located inside the triangle ΔABC. For this to occur, it is enough that all areas of the sub-triangles are positive. Based on these concepts, it is initially possible to identify the position of the virtual sensor (P) concerning three physical sensors (A, B, and C). In the first case, the point P belongs to one of the segments of the ΔABC; for example, in Figure 1 where $P \in \overline{AB}$, we have that ΔABP is defined as a degenerated triangle. In this situation, to estimate the position of the point P, the linear polynomial interpolation method between the points A and B (a first-degree polynomial) will be used through the following relation:

$$\frac{y - y_A}{x - x_A} = \frac{y_B - y_A}{x_B - x_A}. \quad (2)$$

Then

$$y = y_A + (y_B - y_A)\frac{x - x_A}{x_B - x_A} \text{ at a point } P = (x, y) \quad (3)$$

which can be derived geometrically from Figure 1. This function represents, by approximation, a supposed function that would initially represent the images of a discontinuous interval contained in the domain.



(a) (b)

Figure 1: First case.

On the other hand, in the second case, the hypothesis of a non-degenerated triangle ΔABP is addressed; it is assumed that P is not aligned to the points A and B. Therefore, a new condition is assigned, requiring this virtual sensor to triangulate among three physical sensors (A, B, and C). For this, the areas of the sub-triangles must be all positive (Figure 2). If it is identified that the point P is external to the triangle, new vertices are assigned until the desired hypothesis is found. In order to generate a mesh with good formal patterns, the Delaunay method (Chew, 1989) and the barycentric method (Pait, 2018) are initially considered, which use the concept of dividing a notable point known as the barycenter. The barycenter of the triangle is the noteworthy point of intersection of the three medians known as the center point of weights. This method has an advantage in mesh mapping as well as a good convergence acceleration of the method. However, for the application of this method, a refinement of the mesh would be necessary, with the use of successive points to obtain new internal nodes in the mesh, defined as a barycentric subdivision. Note that the greater the number of elements in a mesh, the more costly and slower the computational simulation. This situation is not interesting for the feasibility of this study, which seeks to interact in remote locations with low computational resources. Given this fact, the option of this method will be re-adapted to a technique that will reduce the computational requirement and keep the data to a desirable standard. However, the position of the virtual sensor being restricted only to the barycenter of the physical sensors limits the problematization approach. In this sense, an alternative is to define the point P from barycentric coordinates (u, v and w) in relation to the triangle ΔABC. It means that point P is defined through the weighted average of the vertices of the triangle with weights u, v and w, that is,

$$P = \frac{uA + vB + wC}{u + v + w} = (u : v : w). \tag{4}$$

Therefore, the proposed technique moves the barycenter to the P point of interest, defined by the barycentric coordinate. Thus, it is possible to apply multivariate interpolation (three linear interpolations) based on the straight line from the angle that intersects the opposite line.

Figure 2 demonstrates this process. In Figure 2 the point is defined inside the triangle. In Figure 2 the first linear interpolation is performed. Figures 2 and 2 present the linear interpolation of the other two lines. In the end, the three interpolated values are averaged in order to estimate the value of the virtual sensor P.

4 EVALUATION AND DISCUSSION

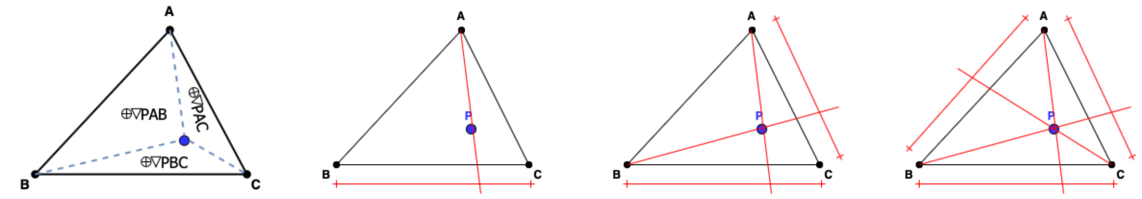
In this section, we evaluate the effectiveness of our method in estimating the values of virtual sensors in IoT environments. We start by describing our setup (§4.2). We present the following experiments: (i) we conduct a sensitivity analysis to find the best set of parameters to the compared algorithms (§4.3), and (ii) we assess the performance of our proposal against other algorithms (§4.4).

4.1 Case Study: Smart Farms

Population growth and technological advances have led the agribusiness sector to invest in new methods, processes, and innovative equipment to produce more and better. In practice, the Smart Farm concept demonstrates these advances in the sector, where information and communication technology has become strong allies of rural producers. The purpose of adopting this new farm concept is to improve efficiency and expand the sector's productivity. The demand for food has increased considerably, along with the delivery speed (Memon et al., 2016). The Smart Farm is based on the insertion of the countryside producers and their activities in totally digital and instantaneous information, enabling faster and more assertive decision-making. For example, smart cameras are already part of the farm's reality. They have an internal computer that can identify an image through its format and colors and alert the farmer of possible risks to the plantation. When a threat appears, the camera sends warning signals and messages via SMS, email, and audible tones. With this, the producer can avoid damage and take action quickly. Such threats can be people wanting to steal supplies, equipments, or even animals.

Another application is the use of drones in production control and evaluation. The device, which can be interconnected with a real-time image observation system, has been used to detect pests, diseases, planting failures, and so on. From the top, the view of the entire production is much broader and can be zoomed in if necessary to observe some detail closely. By positioning the drone at the top, it is also possible to visualize the plant's color, detect the presence of fungi, and take photos to assist the agronomist in the analysis. In addition, the drone also helps to monitor crop development in real-time, making the analysis much more effective than monitoring via car or motorcycle. With the images captured, it is possible to carry out a chronological analysis of the planting, helping devise strategies for greater productivity, such as choosing better soil collection points for analysis. Smart Farms also may present built-in sensors at all stages of cultivation and in their equipment. In this way, when traveling through the field, they can collect different types of data, such as light levels, soil conditions, irrigation, air quality, and climate. The farmer can analyze them and make preventive decisions based on these data. Streamlining repetitive tasks also became possible through robots programmed through their sensors. They entered data to walk across the entire field and work autonomously, weeding, watering, pruning, and harvesting.

Sensors are often the smallest and most fragile components of this intelligent environment. In most cases, sensors are geographically distributed and exposed to weather effects. It can lead to failures, and consequently, impact productivity. Another factor that this article addresses is those places that are difficult to access and where it is not possible (or challenging) to place a sensor to carry out the measurement, for example, very high treetops or at the bottom of dams. It can delay or even derail important alerts for the production environment. This article aims to overcome the issues addressed above and proposes modeling and estimating values through virtual sensors that will be consumed by edge devices. The proposed modeling is performed empirically, based on values obtained from physical sensors around the point of interest (virtual sensor). Virtual sensors are not new within the ICT area (e.g., intelligent agents



(a) (b) (c) (d)

Figure 2: Second case.

and monitoring software). Still, it has been emerging as an option that fits very well in IoT environments.

4.2 Experimental Setup

We compare our method with two well-known distance-based data imputation techniques, k-Nearest Neighbors (kNN) (Fix and Hodges, 1989), and Inverse Distance Weighting (IDW) (Franke, 1982), and a naive triangulation-based algorithm. Both kNN and IDW estimate values based on the values of nearby elements (in our context, physical sensors) with available data. While kNN estimates the values of virtual sensors based on the arithmetic mean of the values of their k nearest neighbors, IDW weights the known observations of the k nearest neighbors based on their distance to the virtual sensor so that closer neighbors get more influence on the inference. The naive triangulation algorithm iteratively creates a mesh of triangles using the Delaunay algorithm and uses the first triangle it finds that surrounds the virtual sensor to estimate its value.

Our evaluation uses a real dataset with observations of 80 weather stations from the south region of Brazil maintained by the National Institute of Meteorology (Inmet). Each weather station contains 8784 data points collected hourly during 2020 describing temperature, atmospheric pressure, and relative air humidity. According to INMET, this dataset is used to drive strategic decisions in the country's agriculture sector. Table 2 presents statistical information about the dataset. We intentionally omitted data from some arbitrary weather stations in the dataset during the experiments. After the tests, we compare estimated values from the evaluated techniques to the actual measurements to assess the accuracy of inferences.

We evaluate the accuracy of compared techniques based on two well-known error metrics: (i) Root Mean Square Error (RMSE), which is given by $\sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i-y_i)^2}{n}}$ and measures the differences between n predicted values $\hat{y}$ and the expected values y based on the square root of the average of squared errors, and (ii) Mean Absolute Error (MAE), given by $\frac{\sum_{i=1}^{n}|\hat{y}_i-y_i|}{n}$, that measures the average of the absolute errors. While both metrics help measure inferences' accuracy, a few large errors in a set of observations will increase the RMSE to a greater degree than MAE, as it squares the differences before calculating the average error. In our experiments, we use MAE to account for the overall accuracy of the techniques. At the same time, RMSE helps us identify the techniques' ability to achieve steady results while estimating the values of virtual sensors in different locations. We build a discrete-event simulator that leverages object-oriented features of Python language to mimic the behavior of weather stations from the INMET dataset. We conducted the experiments in a host machine with a quad-core Intel processor i7-8650U@1.9GHz and 16GB of RAM running a Linux Ubuntu 20.04.2 LTS (kernel 5.11.0-25-generic) and Python 3.8.10. We assume that all of these algorithms are present in the edge servers that collect the data and can, in real-time, fill the missing sensor data gap with data from virtual sensors. Our simulator and the dataset used during the tests are publicly available in our GitHub repository[1].

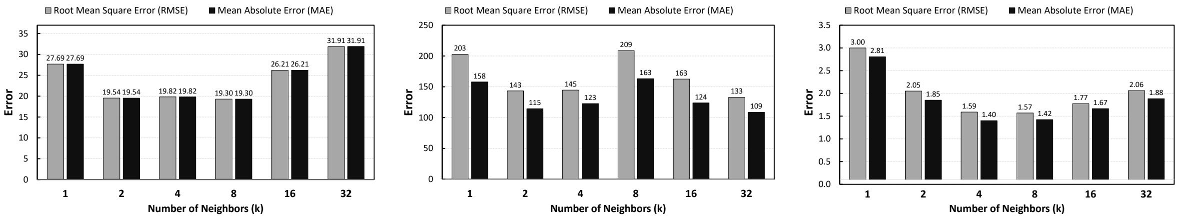
4.3 Sensitivity Analysis

Before comparing the algorithms, we evaluate how the number of neighbors k affects the performance of distance-based algorithms (kNN and IDW). To this aim, we execute these algorithms with different values of k, assessing their RMSE and MAE in the three evaluated scenarios. As shown in Figures 3 and 4, $k = 8$ leads to the best results for both algorithms when estimating the values of virtual sensors regarding atmospheric pressure and temperature, which have less dispersed data (see the standard deviation in Table 2). In these scenarios, narrowing the number of neighbor sensors used to perform inferences affects the accuracy of algorithms as sensor values are more or less uniformly distributed based on their geographical position. On the other hand, $k = 32$ was the best parameter for estimating global solar radiation. Such a scenario comprises more sparsed data, which favors

[1] https://github.com/paulosevero/virtual-sensors-triangulation

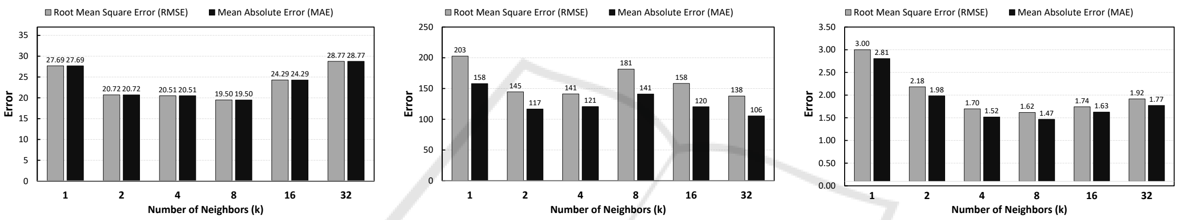
Table 2: Statistical information about the dataset.

Scenario	Mean	Standard Deviation	Minimum	Maximum
Temperature	13.9526	4.2081	-20.9	32.1
Atmospheric Pressure	960.8239	43.3078	811	1027.7
Global Solar Radiation	1467.0968	1111.4419	0	4806.6



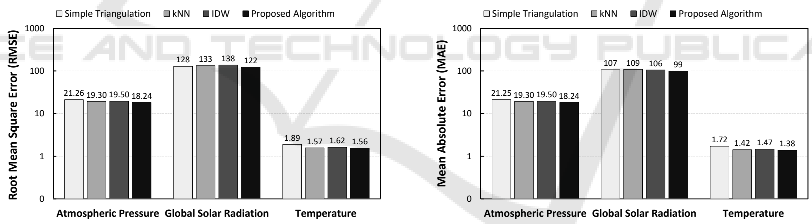
(a) Atmospheric Pressure (b) Global Solar Radiation (c) Temperature

Figure 3: Sensitivity analysis of k-Nearest Neighbors (kNN).



(a) Atmospheric Pressure (b) Global Solar Radiation (c) Temperature

Figure 4: Sensitivity analysis of Inverse Distance Weighting (IDW).



(a) Root Mean Square Error (RMSE) (b) Mean Absolute Error (MAE)

Figure 5: Accuracy results of the compared algorithms.

more neighbors during the inference of virtual sensors.

4.4 Simulation Results

Looking at the results in Figure 5, we notice that the error rates of all techniques grow more or less linearly based on the degree of dispersion of data points of the evaluated scenarios (atmospheric pressure, global solar radiation, and temperature). Accordingly, all strategies achieve higher accuracy when estimating temperature and atmospheric pressure, as these scenarios have lower standard deviation than the global solar radiation scenario. Among the compared methods, kNN and IDW were the most impacted by data dispersion. They estimate the values of virtual sensors based on the average values of k nearest sensors with known data, which allows spread observations to disturb their calculation. As such, kNN and IDW had the worst results in terms of RMSE in global solar radiation, as it presents the highest standard deviation amongst the evaluated scenarios.

While kNN and IDW fall short on providing accurate inferences about the global solar radiation of virtual sensors, the triangulation-based methods manage to get lower error rates by estimating the value of virtual sensors based on reference points created with an interpolation that is located closer to the virtual sensor than the physical sensors in the environment. The main reason behind the superior results of the proposed method against the Simple Triangulation relies on which triangle is used to estimate the value of virtual sensors. While Simple Triangulation picks the first triangle it finds surrounding the virtual sensor, the proposed method goes further and looks for the triangle comprised of physical sensors closer to the virtual sensor. In that way, the proposed method manages to get more accurate linear interpolations, resulting in superior results (RMSE 4.87% lower than Simple Triangulation).

When estimating the temperature of virtual sensors, Simple Triangulation exhibited the worst results, ignoring the distance between the virtual sensor and the points used in the triangulation. On the other hand, the lower data dispersion in the dataset favored IDW and kNN that managed to get the third and second-best results. Once again, the proposed method achieved gains of 0.7% and 2.9% in terms of RMSE and MAE compared to the second-best solution (in this case, kNN) by inferring the value of virtual sensors based on interpolated values of nearby reference points within the triangles it generated.

4.5 Potential Impact on Smart Farms

The applicability of virtual sensors on smart farms allows the analysis of data referring to a target without direct contact with it through mathematical resources based on real optical-electronic sensors. In addition, virtual sensors will enable the creation and filling of reliable data in maps of areas with no real sensors. It is vitally essential for monitoring sparse areas and over metrics measured by geographically remote devices. Tools that use virtual sensors facilitate data collection in the regions that are difficult to access and collaborate with the monitoring of dynamic processes in nature. Several advantages make IoT-Edge an important issue, especially in the current context of society, as it can show geographic and historical data relating to natural and social spaces. In addition, we currently discuss environmental preservation as a global agenda in various educational and political events around the globe and used in the monitoring and analysis of natural resources. Among the most relevant areas in which virtual sensors can positively affect production.

One of the leading practices of virtual sensors is associated within its use in Agriculture, as this technology has great potential, as it is possible to obtain various information such as estimated planted area, plant and crop health, pest detection in the plantation, and observation of the production process, plant counting, soil cover analysis, etc. The virtual sensor can become one of the main tools of precision agriculture because monitoring agricultural production can provide productivity results never achieved and reduce several operating costs. In addition, virtual sensors can be used to analyze and monitor risk areas, enabling the control of hurricanes, erosion, and floods through satellite images and geoprocessing techniques and the meteorological monitoring of the earth and follow natural events. Through aerial images, it is also possible to assess the impacts of natural disasters and allow strategies for prevention, combat, and rescue. For example, drones with multispectral cameras can identify hot spots in cave-in zones and indicate survivors.

For forest areas, virtual sensors can be used to analyze data regarding the distribution of forest areas, advance deforestation activities, calculate volumes, identify species, etc. Considering how relevant the theme of environmental preservation has become in recent years, especially in the world's political environment, virtual sensors can become a fundamental tool for decision-making in the management and management of natural resources, such as analyzing and monitoring water resources, calculating and estimate physical and chemical parameters of soil and water, determine the climatic characteristics of a region, identify critical points in anthropized areas, determine the region's relief, observe the behavior of fauna in a region of interest, etc.

5 CONCLUSION AND FUTURE WORK

Virtual sensors have internally implemented a model with secondary input variables that can be measured and output the variable of interest inferred. A virtual sensor can infer values from positions where there are no real sensors or where real sensors are inactive. In this work, we proposed new modeling and implementation of virtual sensors based on the real sensor values consumed by edge servers. The results of our model were superior in terms of accuracy compared to proposals in the literature based on IoT-Edge ecosystems. To test our proposal, we used a well-know IoT environment, a Smart Farm scenario.

Based on simulations using real-world traces, we observe that our method can estimate the value of virtual sensors with a high degree of accuracy, reducing the RMSE and MAE by up to 5.5% and 5.8%, respectively, compared to existing approaches. In future work, we intend to incorporate a multivariate technique that uses multiple correlated variables from nearby locations to estimate the value of virtual sensors.

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