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Parallel Design of a Product and Internet of Things (IoT) Architecture to Minimize the Cost of Utilizing Big Data (BD) for Sustainable Value Creation

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Abstract

Information has become today's addictive currency; hence, companies are investing billions in the creation of Internet of Things (IoT) frameworks that gamble on finding trends that reveal sustainability and/or efficiency improvements. This approach to "Big Data" can lead to blind, astronomical costs. Therefore, this paper presents a counter approach aimed at minimizing the cost of utilizing "Big Data" for sustainable value creation. The proposed approach leverages domain/expert knowledge of the system in combination with a machine learning algorithm in order to limit the needed infrastructure and cost. A case study of the approach implemented in a consumer electronics company is also included.

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Keywords: Internet of Things; Big Data; Product Design; Machine Learning; Sustainability

1. Introduction

In today's Big Data (BD) craze, companies are going "all in" on big data. They are investing billions in Internet of Things (IoT) infrastructures and the necessary personnel to support them. These companies are looking for diamonds (i.e., efficiencies and cost savings) in the rough (billions of unstructured data points) in order to justify the added investment and ongoing costs. More specifically, the manufacturing sector has seen considerable research in this area because the industry generates a large amount of unstructured and structured data that ideally can be processed and then used to achieve significant improvement in product design, manufacturing efficiency, cost reductions, scalability, resiliency, and environmental sustainability [1,2].

However, many of the companies that have been banking on big data still do not have much to show for their efforts [3]. In fact, those same companies have not even cashed in on the information systems that that they put into place 10-15 years ago [3]. The current approach of creating these extensive IoT frameworks involves outfitting legacy products, processes, and systems with numerous sensor nodes and IT systems in order to collect a significantly large dataset, only to have a fraction of it filtered into a usable state. Although excellent in theory, this approach can lead to an astronomical initial investment that could hinder any practical implementation into a production environment. On the other hand, if this approach is implemented blindly, there is a great risk associated with managing the new overhead. This trap is caused by the idea that information is free. While information is free, the ability to access it and use it in a way that can be beneficial is far from free. Everything from collecting the data points, to processing, and then storing them has an associated cost. For example, if only one million data points out of the original one billion is actually usable in a way that they can see a return on investment, then there was a waste of 99.9% of the data collected.

With that in mind, there is a need for a counter approach to implementing big data that can minimize the cost in order to realize sustainable value creation. Therefore, this paper

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presents an approach that is comprised of leveraging domain/expert knowledge of a system, product, and/or process in combination with an advanced machine learning algorithm. The premise of the approach lies in consolidating the functionality of the system into minimal hardware and physical infrastructure. By designing the system hardware in parallel with the IoT architecture, the amount of data collected can be trimmed to the amount that will actually be used.

2. Previous Work

For years, the vision of the IoT and its impact on product design and manufacturing has been being molded for future implementation. It can be said that the IoT is a means for aligning the physical and information life-cycles [4]. This vision suggests that this intimate connection and the information itself presents a major source of value [4, 5]. Dubey et al. [6] suggest that Big Data (BD) is one of the emerging research areas that are considered “game changers” in the manufacturing sector. The claim is that the use of big data can see a 15-20% increase in return on investment and surplus cash for customers [6].

Looking at IoT and BD through the lens of sustainability, the sought-after gain from such an implementation is information that mainly aims at reducing energy and resource consumption. However, there must be a balance of the amount of energy and resources used to build the required infrastructure and support system in order to prove a net improvement [7]. In addition, it is suggested that improvements to sustainability can also come in the form of combining multi-source information, and then making a calculated decision from that information using cloud computing and web services [8]. Although many companies are going after cost reductions, those reductions will inevitably give way to the law of diminishing returns. Because of this, other companies have seen better results utilizing big data in sales, marketing, and research and development in order to increase profits indirectly [9].

There have been several case studies involving the use of IoT and BD in order to drive sustainable value creation. In Pan et al. [10], a framework is built surrounding the HVAC and building industry and the use of IoT systems to improve energy usage. The approach envisions creating significant economic benefits, as well as social and environmental benefits. Tao et al. [11] presents an integration between an IoT system and a traditional PLM system. This work provides an idea for collecting environmental and life-cycle data throughout the entire life-cycle. The work also proposes the idea of a big Bill of Material (BOM) that uses the integration interface with the IoT systems in order to exchange and transform information. The next case considers the idea of using cloud based technologies in order to support product services [12]. In other words, a decision support system is built on top of the BD foundation. In other cases, these services are built to be proactive by building in predictive models and analytics into the decision support system [6].

Another case is seen in the food production sector where the application of BD to the supply chain can have implications for many industries. The work claims that analytics can translate customer requirements into an increase in sales, by being able to mine the rationale from metadata. In addition to the positives, the utilization of BD results in negatives as well. For example, tailored consumer level detail can result in the loss of purchasing options among other things [13].

Cost, energy, and resources have been discussed extensively, yet water is considered sparingly. The work by Koo et al. [14] advocates using the IoT technology for sustainable water development. The proposed solution consists of using sensors that capture water data through a virtual platform and control system. This work established three benefits: leak detection/prediction, optimization of production, and optimization of consumption.

3. Proposed Approach

The proposed approach for implementing an IoT system for sustainable value creation consists of leveraging domain/expert knowledge of a product, process, and/or system by the means of parallel design of the system hardware and the IoT architecture. In addition to the co-design element, the other essential component to the proposed approach is combining the domain/expert knowledge with a machine learning algorithm. This machine learning algorithm allows for more information to be extracted from the IoT sensor network than what would traditionally be measured.

For example, in a traditional IoT system you may have Node 1 measuring time, Node 2 measuring value “A”, Node 3 measuring value “B”, Node 4 measuring value “C”. However, with this approach, because the system is being designed in parallel, one is aware through an understanding of the physical system that Node 2 can be slightly altered to be a dynamic measurement and a function of time. With that alteration combined with the use of a machine learning algorithm, Node 2 solely becomes able to represent time and values A, B, and C. This paradigm suggests that the number of sensors does not have to be equal to the number of measured values.

The overall approach can be seen in Figure 1, where the product, process, and system are being designed in parallel

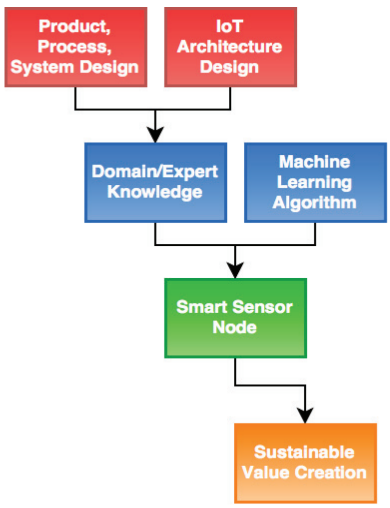

Fig. 1 Overview of the Proposed Approach

and that knowledge gained can then be seen joined with the machine learning algorithm. This approach suggests that the overall cost and associated footprint of an IoT system can be reduced by deploying the proposed method.

The traditional approach, shown in Fig. 2, is outfitting a physical system with a complex network of sensor nodes in order to collect a large amount of data coinciding with various attributes of the system. In this figure it can clearly be seen that there are four nodes that are collecting data and storing that data in the cloud. There are two issues with this setup: 1) It requires hardware for all 4 nodes, 2) The data is stored in the cloud and must sifted through to come up with the needed subset. This results in an inflated system with considerable amount of resources and energy being required for the hardware, as well as a large amount of required processing in order to consume the data. With that in consideration, this setup shows that there is much left to be desired in terms reducing the overall cost and footprint of such a system.

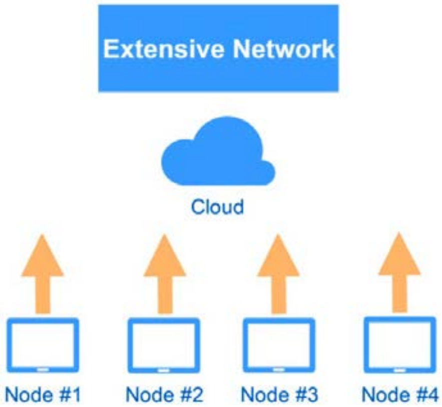

Fig. 2. Traditional Extensive IoT System

On the contrary, the proposed counter-approach can be seen in Figure 3. In this approach, the four nodes have been consolidated into a single node through the use of domain expert knowledge of the physical system. In addition, this product, process, & system knowledge is used in combination with the machine learning algorithm in order to reduce the overall footprint of the system from a cost, energy, and resources perspective. In addition, the machine learning algorithm can be imposed directly at the point of the node itself. Although this may not be applicable for every application, it can present a unique advantage over large volumes of cloud computing. Therefore, this solution offers economic, environmental, and societal benefits and identifies as the more sustainable option to be put into practice.

With the consideration of the proposed approach and the possible benefits, there is a need for the application of the approach in a case study. The case study shown in the next section validates the limit in infrastructure, offers a cheaper implementation with sustainability improvement.

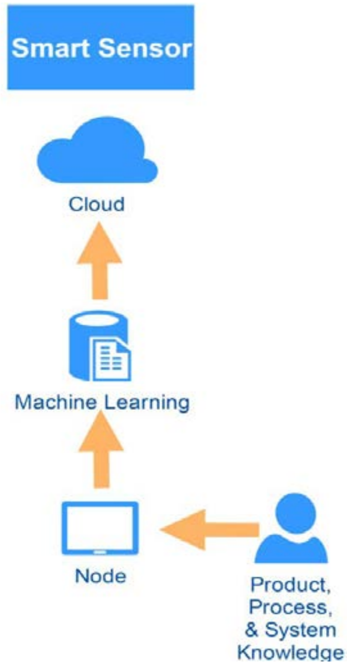

Fig. 3. Proposed IoT System

4. Case Study

4.1 Motivation

This case study looks at the proposed approach as applied to the consumer electronics industry, more specifically, the consumer printing and managed print services industry. In the managed print services industry in particular, there is a push for the development of proactive and predictive service management programs that can help mitigate field service issues seen with many printing devices. As part of this larger effort, the system that was designed in this case was an automatic media type classification system that keeps users from having to change the settings themselves.

Looking at the facts, it has been determined that a majority of the users of printing devices never check or adjust the media type settings. In addition, out of those users that do check or adjust the media settings at least some of the time, only fraction of them select the correct settings. Incorrect settings on these devices can cause detrimental problems for both the customers and manufacturers in all three pillars of sustainability. First, wrong settings during the operation of the device can cause damage to the machine, resulting in a service call that can lead to astronomical costs. In addition, wrong settings can result in unneeded energy use, numerous wasted sheets of paper, and an overuse of toner. These wastes represent both cost and an environmental impact. Lastly, wrong settings significantly impact the print quality of the device and can cause negative experience for the customer and unneeded service calls for the manufacturer. Therefore, the studied application looks at a system internal to a printing device that aims at determining the correct media moving throughout the machine. This case-study also lends itself well to the manufacturing industry. The printing process, although internal to a consumer product, can be imagined as a small-scale manufacturing process and therefore contains strong similarities to that of a manufacturing line.

4.2 Preliminary Implementation

Prior to devising the proposed methodology, the mindset surrounding the solution was very much in line with the traditional approach of outfitting the device with numerous sensor nodes in hopes to collect as much data as possible. In this case, the preliminary implementation looked at using four different sensor nodes to capture various measurements of the paper: bending stiffness, optical translucence, density, and electrical impedance. All of these measurements are directly related to physical attributes of the media. These attributes contribute to controlling operating parameters that are a function of how various media types interact with the electrophotography (EP) printing process. Figure 4 shows the original sensor nodes and their corresponding properties.

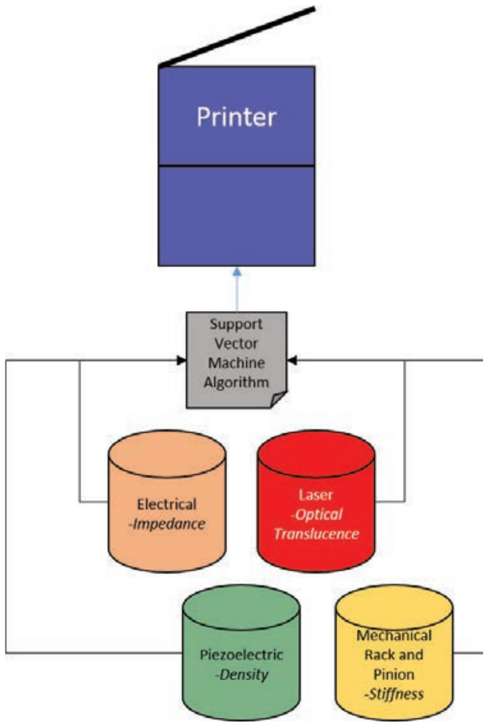

Fig. 4 Preliminary Implementation System

With this system, four total nodes were being considered, all of which were tailored to the purpose of collecting a specific piece of data. These data points were then used as features for a support vector machine that was used as the machine learning algorithm. The limitations that exist with this system are the lofty costs and overall footprint involved with fielding four sensors. Any cost reduction or identified improvement would be quickly swallowed up by the cost associated with the implementation. However, by using the knowledge of the system, a more efficient architecture could be formed.

4.3 Leveraging the Methodology

The four sensor nodes could ultimately be reduced to one sensor node, while not losing any performance. The breakthrough that allowed for this, was expanding the LED/photoresistor being used to capture optical translucence to a dynamic measurement to encapsulate the domain expert knowledge of the printing system. Instead of collecting individual measurements through individual sensor nodes, a smart system was deployed that consolidated all of various media attributes that were being measured with the previous nodes into a singular time-series trace. Figure 5 shows the final solution that was devised.

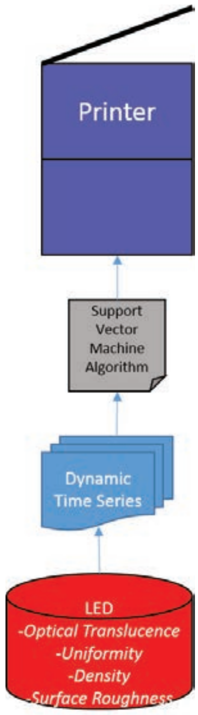

Fig. 5 Final Implementation System

As stated previously, this singular node implementation extracts all properties of the media across the time-based trace of data: optical translucence, media uniformity, sheet density, and surface roughness. Replacing impedance with uniformity and stiffness with roughness, ultimately allowed for the consolidation and similar performance. In addition, the dynamic nature of the measurement allows for a secondary piece of data to be extracted in the form of the media and machine interaction. This interaction adds to the robustness of such an architecture.

In addition to the functionality, the economics are also compelling. The system went from a bloated system that would struggle to justify itself in the form of value-added and operational efficiency, to a more sustainable system that makes up a fraction of the cost, energy, and resources.

To be able to leverage this cheap singular sensor in such a compelling way, one must look at the support vector machine that drove the functionality. Through the dynamic time series data, features were able to be selected in parallel with the knowledge of designing the sensor systems themselves to be able to stretch the sensor hardware and machine learning algorithm to its full potential. Figure 6 shows the feature selection that was determined in order to create the largest separation between the various media types.

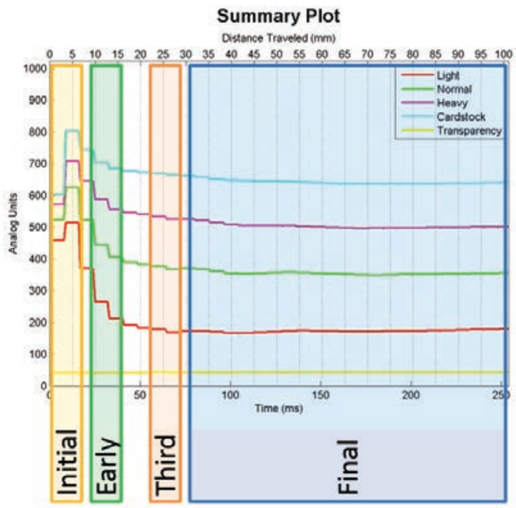

Fig. 6 Support Vector Machine Feature Selection

Four zones can clearly be seen in Figure 6. The separation between the various media types can be seen from the average trace values. Each zone was used to devise statistical metrics that were then fed into the algorithm. The algorithm was subsequently used to make a calculated guess at the paper type in order to be able to set the device to the appropriate operating parameters.

4.4 Results

The five considered media types were trained and then tested with the proposed solution. Overall, 92.23% of media types were determined correctly, and 99.3% were determined to be in a range of satisfactory performance. In addition, it was estimated that real cost savings and reductions in energy, paper, and service action can be realized throughout the product life-cycle.

5. Conclusions

The proposed approach for designing an IoT architecture shows an opportunity for minimizing cost while leveraging big data for sustainable value creation. Many industries can benefit from the counter approach, especially manufacturing due to their unique use of unstructured and structured data to drive improvements in energy efficiency, reduced resources, cost reduction, scalability, and environmental sustainability. A case study was presented that looks at the consumer printing process and a sensor solution that aims at improving the field service issues with various products out in the field. The case study validates the premise of co-designing a product, process, and/or system in parallel with the IoT framework in order to minimize costs and improve functionality. The combination of the domain/expert knowledge and the machine learning algorithm creates a robust framework for use in various applications. Future work can entail extending this approach to other industry sectors to show how big data can be leveraged for sustainable value creation.

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