Data Driven Decision Support for Reliable Biomass Feedstock Preprocessing

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***Abstract*— Biomass feedstock preprocessing through comminution is an essential first step in biofuel production. Chemical, physical and mechanical variability in feedstock prevents the preprocessing plants from assuming constant control parameters. Constant control parameters can lead to suboptimal capability and reliability. However, adapting the control parameters to account for the variabilities is not a trivial task. This paper presents a framework for adapting control parameters through data driven methodologies. The framework named PDU-RS is a decision support system for human in the loop control. PDU-RS is implemented on the Biofuels National User Facility Preprocessing Process Demonstration Unit (PDU), operated by the Idaho National Laboratory (INL) in Idaho Falls, Idaho. PDU-RS aims at ensuring reliability in the overall operations of the PDU while maximizing throughput. Presented implementation of the PDU-RS uses Gaussian Processes (GP) for knowledge extraction from data. This paper elaborates on the PDU-RS and presents the experimental results of implementing the PDU-RS on the real Biomass PDU. The experimental results demonstrated that the PDU-RS is able to produce significantly higher throughputs while ensuring higher reliability when compared to the traditional control methodology used with the system.**

Keywords — Biomass comminution, Gaussian process, Decision support system

I. Introduction

Mechanical size reduction (comminution) of biomass feedstock is a fundamental preprocessing mechanism for production of biofuels. Comminution of biomass helps to increase the bulk density and surface area of biomass feedstock [1], [2].Comminution is necessary to reduce transportation, handling and storage costs [2], [3], [4], which is fundamental for making the biomass industry an economically viable enterprise [5]. Comminution influences pellet durability and densification processes [4].

Size reduction is not only necessary for reducing cost, but it is also required for most of biomass refinery and combustion technologies. For biofuel production, size-reduction is necessary to eliminate mass and heat-transfer limitations during the hydrolysis reactions [6]. Further, it reduces the crystallinity of cellulose and improves digestibility [7]. An increased percentage of small particles also improves ignition and combustion properties of biofuels [3]. For example, corn-stover ethanol production requires particles to be reduced to 0.5 mm to 3 mm [8].

Processing of particle systems, like biomass feedstock and powders, present several challenges. The interaction of particle systems with process equipment can be unpredictable, which makes mathematical models difficult to obtain [9]. Feedstock presents a large variability in terms of moisture content, ash and particle morphology [10]. These highly variable factors are difficult to control and affect the efficiency and production rate of grinding systems [2].

Given the large variability in the feedstock properties, refinement plants usually have to deal with products that were not considered during the design phase [10]. This causes equipment to be operated beyond the original design envelopes, causing inefficient production and common downtimes.

Large-scale production of biofuels requires developing strategies for reliable operation of the equipment involved and being able to reject disturbances induced by feedstock variability that was not considered in the design phase.

Improving reliable and optimal operation of the grinding systems has been primarily addressed for ore comminution [11], [12], [13]. Research on biomass comminution has been instead focused on characterizing the energy consumption and properties of the resultant product for different grinding technologies [1], [14], [15], [16], [17], [18]. Ore comminution and feedstock grinding systems face common problems in the control paradigm. Model mismatches, sensitivity to variations in ore hardness and particle size distribution [11] , [13] and complex unpredictable behavior of particle systems [9] are some of the reasons that have lead researchers to turn into data-driven models for improving the comminution process [11], [19], [20].

Data-driven approaches allow efficient extraction of information and knowledge from large amounts of historical data. These techniques are becoming increasingly popular on large-scale industrial environments for control, monitoring and diagnosis [21], [22], [23]. They provide tools for analyzing and obtaining mathematical models of complex systems when first principles physics-based modeling techniques are either too complicated or do not provide satisfactory results.

In this paper, we present a data-driven recommendation system called PDU-RS. The system provides estimations of the performance of the grinding system for a given feedstock infeed rate, bale moisture content and grinder screen sizes. This allows the operator to make appropriate informed decisions for processing a given feedstock bale, ideally improving the throughput and reliability of the plant. The estimation of the system behavior is built upon available historical data. The system uses Gaussian processes (GP) for obtaining a model of the throughput and reliability of the system as a function of the

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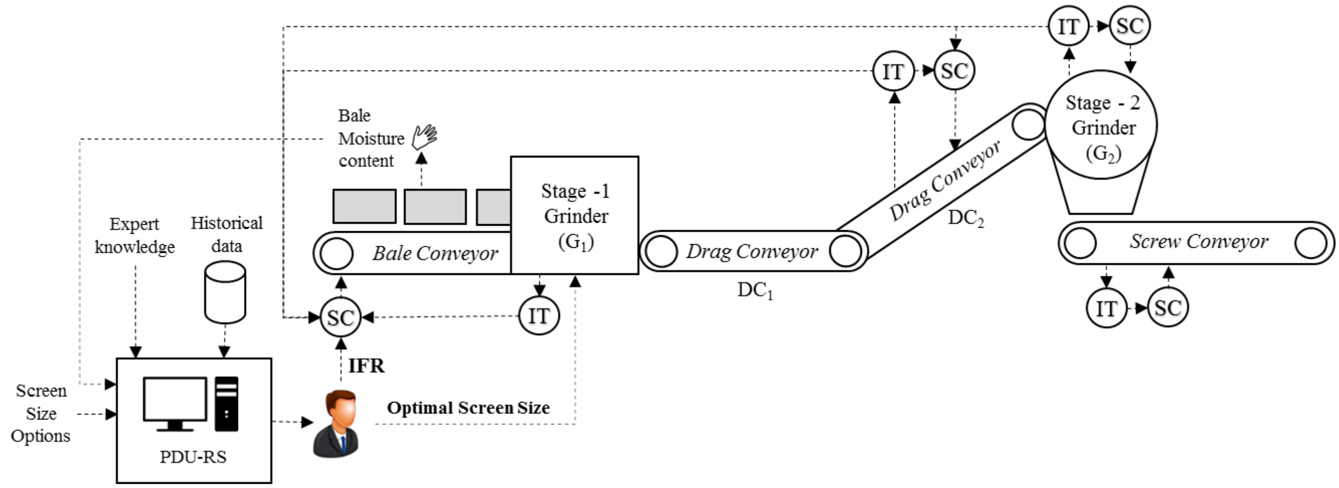

Figure 1: PDU-RS diagram. Key: G: grinder, C: conveyor, IT: current transducer, SC: speed/frequency controller

infeed rate, bale moisture content and grinder screen sizes. Furthermore, GP allow the modeling of confidence (uncertainty) in the predictions. The operator can use the estimations from GP to make an informed decision about the parameters of the plant that would lead to a maximum throughput while reducing downtimes.

The rest of this paper is organized as follows. Section II introduces the PDU and elaborates on some of the control problems. Section III introduces the machine learning techniques used in the PDU-RS. Section IV elaborates upon the PDU-RS. Section V presents control experiments and the results obtained, and finally Section VI concludes the paper.

II. INL Biomass Feedstock Preprocessing Process Demonstration Unit

This section provides an overview of the PDU that is operated by the INL at the Biofuels National User Facility in Idaho Falls, ID and used as a key demonstration within this paper.

The PDU is a full-scale, integrated preprocessing system. The PDU is used for preprocessing feedstock supply and its main role is to reduce bales of biomass feedstock into particles of predefined size distribution. The particle reduction process is handled in two stages, through two main grinders. Grinding screens are used in both grinders and screens can be changed depending on the requirements of the customer. The first stage grinder (G1) has the capability of using five different screen sizes: 6”, 4”, 3”, 2”, and 1” while the second stage grinder (G2) has two different screen sizes: 1” and ¼”. The rate of feeding the bales into the system and the screen sizes are the two primary parameters that can be changed to control the operations of the PDU. The main factor that affects the changes in the plant is the moisture content of the bale. Therefore, the control variables are determined depending upon the moisture content of the bale.

Fig. 1 shows the overall biomass feedstock preprocessing process. As mentioned, the PDU consists of two grinders for the two stages of grinding (G_1 and G_2). Material is transferred with the use of conveyor belts. The biomass feedstock preprocessing is carried out in a pipeline. Prior to comminution the bales are weighed and probed for moisture content. The bales are then introduced into G_1. Once the raw material is ground using G_1, two drag conveyors (DC_1, DC_2) are used to transfer material to G_2. Then G_2 is used to complete the second stage of grinding and the reduced particles are moved to the metering bin through a screw conveyor where the material is stored in preparation for the densification process.

The performance or capability of the system is measured in terms of the systems’ throughput, which is the amount of material that is processed for a given time (measured in tons/hour). The reliability of the system is measured in terms of the time that the system is operational. Reliability of each component (grinders and conveyers) is measured as percentage of the time they were functioning during the grinding process. Component failure is a result of the feedstock variability in their chemical composition, physical properties and mechanical properties [10]. Feedstock variability results in different material deconstruction behavior during preprocessing. These problems include plugging of grinding screens, overloading grinders, plugging of conveyors and increased wear and tear of the grinders. Figure 2 shows a plugged screen in one of the grinders. The primary cause of these problems is that the preprocessing control parameters typically do not adapt to the variable feedstock inputs. Therefore, adapting of control parameters depending upon the feedstock variability is of

Figure 2: Plugged screen

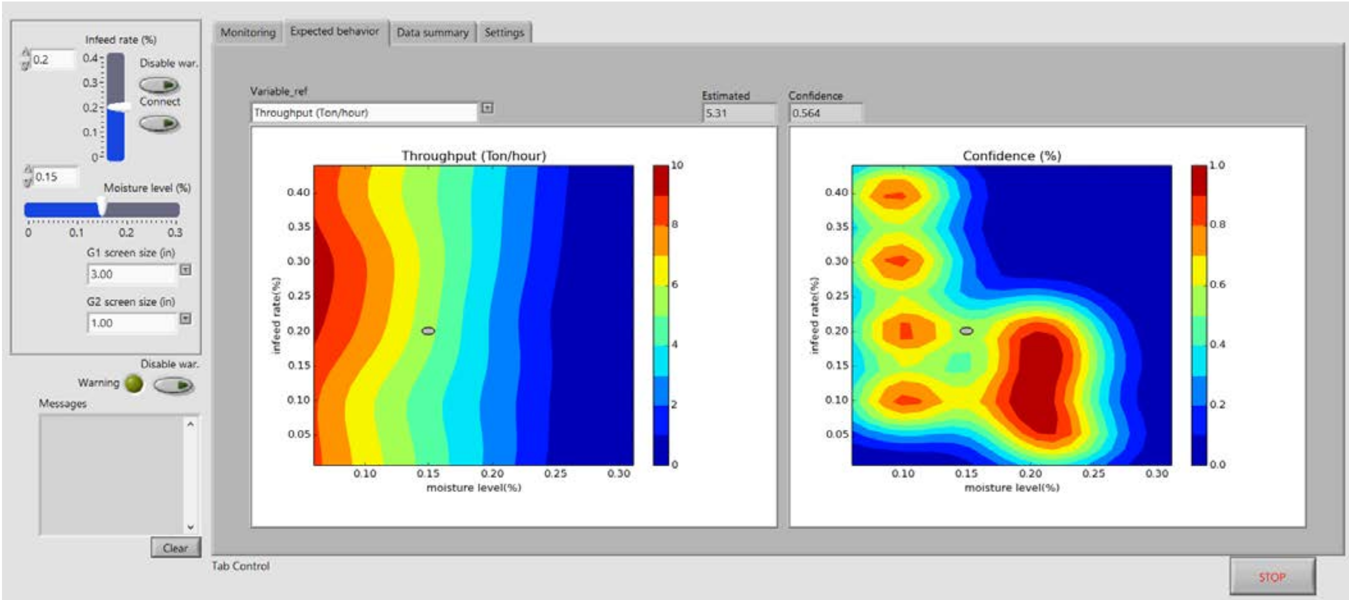

Figure 3: PDU-RS displaying the estimated throughput and the confidence of the estimation to the user. Percentages are represented between zero and one

absolute essence to prevent the PDU from failing and to prevent sub-optimal performance.

As material is introduced into the process, bale weight and moisture content is provided to the operator. Also, each of the conveyors and grinders have real time usage indicators available to the operator, ultimately allowing the monitoring of the health of the PDU. The indicators include primarily motor currents of the components and a product level sensor for the drag conveyors. These indicators are compared to predefined thresholds. If the indicators exceed thresholds on a consistent basis, the operator can adjust the control parameters to bring the PDU operations back to "safe" conditions. Therefore, real time monitoring is extremely crucial for the PDU.

Therefore, the goal of the presented work is to minimize the percentage of time that components are not functioning while maximizing the material throughput of the system. To that end, bale infeed rate (IFR) and G_1 and G2 screen sizes are used as the primary control parameters, while bale moisture content (BMC) is used as the feedstock variability indicator. PDU-RS recommends optimal values for the IFR and the screen sizes depending upon the BMC before operation starts.

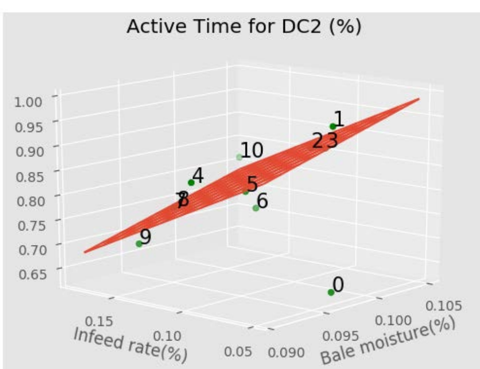

Figure 4: Robust linear regression for extracting the linear prior

III. Gaussian Processes

This section provides a brief background on Gaussian Processes (GP). GP are used for data driven recommendations for the PDU-RS.

GP provide a flexible framework that allows for designing data-driven models using Bayesian analysis [24]. A Gaussian process is specified through a mean function $\mu(x)$ and a covariance function $k(x,x')$, which together provide a model for a stochastic process $f(x)$:

$$f(x) \sim \mathcal{GP}\big(\mu(x), k(x,x')\big) \tag{1}$$

Given a training dataset X and a testing dataset X_*, the Gaussian process assumes the samples are drawn from the following joint prior Gaussian distribution:

$$\begin{pmatrix} f \\ f_* \end{pmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu \\ \mu_* \end{bmatrix}, \begin{bmatrix} K_y & K_* \\ K_*^T & K_{**} \end{bmatrix}\right) \tag{2}$$

where $\mu(X)$ represents the mean for the prior. $K = k(X,X), K_* = k(X,X_*), K_{**} = k(X_*,X_*)$ are the matrices obtained by evaluating the kernel $k(x,x')$ on the training and test datasets.

The function $\mu(X)$ can be thought of as the default output of the model when no data is available. Most of the applications involving GP assume $\mu(X) = 0$, which intuitively represents zero as the expected output when no data is available.

From the properties of Gaussian distributions, given the training dataset $\{f, X\}$, the posterior probability distribution of the outputs of the test dataset is expressed as follows:

$$p(f_*|X_*, X, f) = \mathcal{N}(f_*|\mu_*, \Sigma_*) \tag{3}$$

$$\mu_* = \mu(X_*) + K_*^T K^{-1}\big(f - \mu(X)\big) \tag{4}$$

$$\Sigma_* = \Sigma_{**} - K_*^T K^{-1} K_* \tag{5}$$

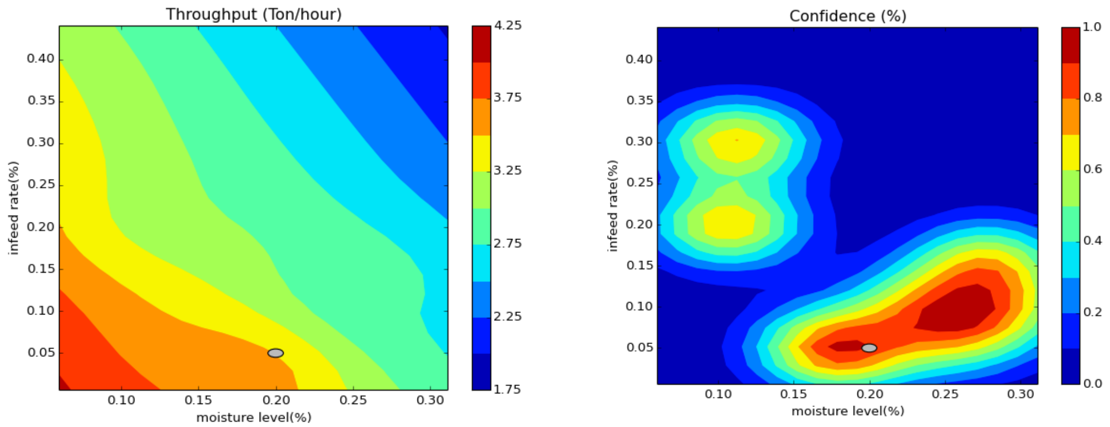

Figure 5 a) Throughput using a screen size of 6” in G_1

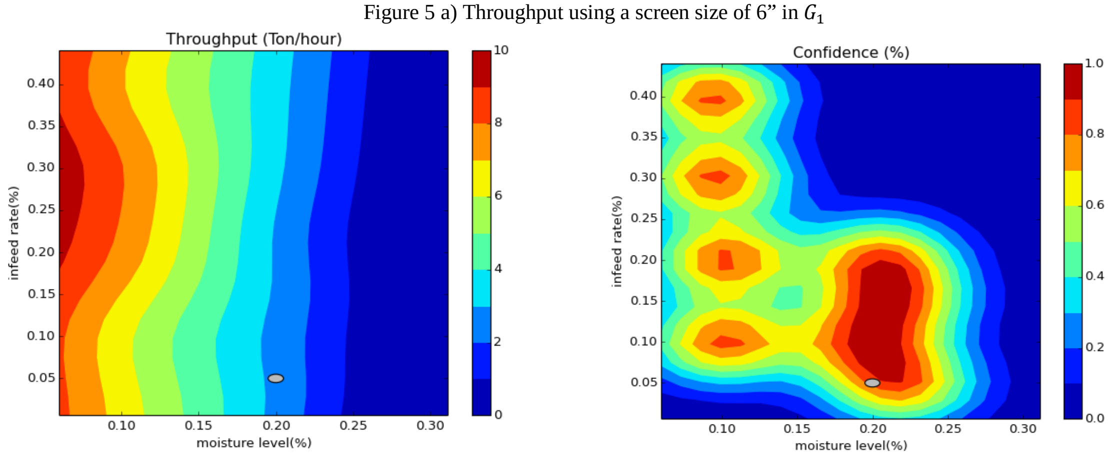

Figure 5 b) Throughput using a screen size of 3” in G_1

IV. Intelligent Decision Support for Biomass PDU

This section discusses the PDU-RS decision support system.

The PDU-RS provides recommendations to the operator for the control variables given the attributes of the bale that needs to be processed. PDU-RS uses a GP based methodology for making recommendations to the operator. Figure 3 shows the PDU-RS interface. The GP based methodology is used to provide estimated results for throughput and system reliability for the recommendations. In addition to the estimations, the PDU-RS provides the confidence of the estimations.

In the current implementation of the PDU-RS, IFR to the system and the Grinder screen sizes are considered controllable variables for the operator.

A. GP based performance estimation

GP provided a data-efficient model that was used to obtain estimations of performance and reliability while providing the confidence of the estimations.

The PDU-RS uses GP for obtaining a model of the following variables: system throughput; average current on grinders and conveyors; standard deviation of the currents for grinders and conveyors; percentage of active time for grinders and conveyors; mass-flow in DC_1.

The PDU-RS uses a linear mean function $\mu(x)$ as opposed to a zero mean for the prior distribution. This assists in providing more accurate predictions in non-explored spaces, based on the trend of data.

Although in the Bayesian setting, the prior distribution is used to introduce *assumptions* of the model before taking into consideration the sampled data. For this application, linear $\mu(x)$ extracted from data was used in the prior distribution to provide a high bias model that can provide better estimations when extrapolating, while the Gaussian kernels will provide local expressive models for modeling local non-linear behaviors.

Given that the data is often corrupted by noise that is not normally distributed, e.g. incorrect annotations, instead of standard L_2 linear regression, we used a Huber function loss to attain robust linear regression when extracting $\mu(x)$[25]. Figure 4 shows the benefits of using robust linear regression for identifying data outliers.

Using a linear $\mu(x)$ provides a tool for getting estimations of infeasible regions outside the explored space. In the case of throughput, regions with zero values suggest operation points where the system is unable to operate. These estimations provide a tool for warning the operator about harmful settings that might reduce reliability and capability.

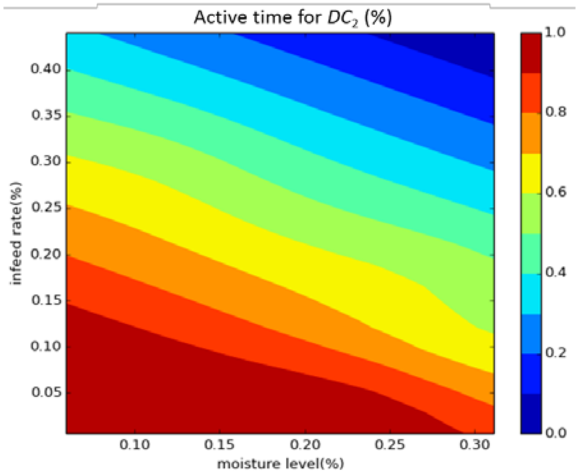

Figure 6: Percentage of active time for DC_2

Providing the confidence of the estimations allows the operator to visualize the explored configuration space. Modeling confidence provides a tool for warning the operator about, possibly, incorrect estimations on regions where data is no available. For improving understanding of the user interface, the confidence is presented normalized between zero and one, where high confidence corresponds to regions where historical data of the process is available.

Fig. 5 shows how GP provide information of previously explored space, estimations based on the trend of the data, and local non-linear variations on explored areas. The model provides a tool for making informed decisions about the infeed rate and screen sizes that should be used for a particular bale in order to increase throughput while maintaining a reliable operation.

V. Experimental Results

In order to test the effectiveness of the developed PDU-RS, five different tests were carried out. Table 1 summarizes these tests. Tests were designed to cover the different scenarios that can arise in the real word operation of the PDU system. Tests one to three were designed to determine the performance for each of the base moisture cases. Tests four and five were designed to check the adaptability of the PDU-RS for a mixed set of bale moistures. For the tests, it should be noted that a 1" screen was used at the stage two grinder (G_2) as INL has learned that this is more aligned with industry requirements and is actually more challenging to achieve.

Apart from Test 1, all the tests were run with the screen sizes and IFRs recommended by the PDU-RS. For test 1, the screen size was fixed by the operators and only the optimal IFRs were recommended by the PDU-RS.

Fig. 5 presents the estimations for throughput using a screen size of 6" and 3". These figures provided valuable information to the operator about the expected performance of the system and the effects of the properties of the bale. For example, Fig. 5.b. shows the high dependency of the throughput with respect to bale moisture content.

Fig. 5 demonstrates how the PDU-RS was used for choosing the screen size for a particular bale. For low moisture bales, the GP model estimated that a 3" screen provides higher throughput than a 6" screen. In contrast, for high moisture bales, PDU-RS estimates the 3" screen will be unable to process the bale, hence the 6'' screen is preferred.

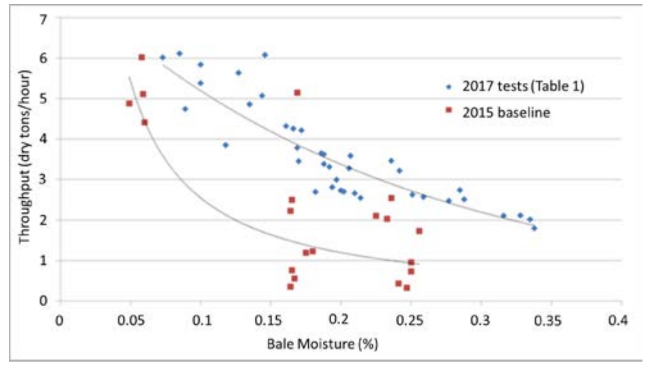

Figure 7. Moisture vs Capability

Fig. 5.b. shows the advantage of using a linear $\mu(x)$ for the prior distribution. Even when data is not available for high moisture bales using a 3" screen, the model can extrapolate and provide estimations based upon the trend of the data.

The advantages of modeling confidence are also shown in Fig. 5.a, where even when the throughput is maximum at (0, 0), the corresponding confidence is low, indicating that there is no historical data at that point. Therefore, the operator should be careful with the resulting estimations at that point.

Fig. 6 presents the estimations for the percentage of active time (PAT) of one of the motors in DC_2. Estimations of PAT provided valuable information about the reliability of the system running at a particular configuration. Low PAT is a result of shutdowns caused by equipment exceeding the maximum amperage. Therefore, regions with high PAT are desirable for improving the reliable operation of the process.

A common scenario for running the grinding process was to maintain a fixed screen size for the grinders, while tuning the IFR to accommodate for different moisture contents. A simple approach to ensure a reliable operation was to maximize the throughput while maintaining the estimated PAT above a certain predefined value for all the components.

PAT also provided information of which components are more likely to fail during an operation. Components with low estimated PAT were closely monitored during operation. This was extremely important to improve the response time of the operators by focusing their attention to the critical components.

TABLE 1: Test Descriptions

Test No.	Test Description	Screen Size
1	6 Bales, Dry (6-14%)	G_1: 3", G_2: 1"
2	8 Bales, Medium (17-23%)	G_1: 6", G_2: 1"
3	6 Bales, High (25%-32%)	G_1: 6", G_2: 1"
4	6 Bales, mixed moistures, ordered	G_1: 6", G_2: 1"
5	6 Bales, mixed moistures, random	G_1: 6", G_2: 1"

Another important factor for achieving reliable operation was remaining close to previously explored regions. By modeling confidence, the PDU-RS system allowed informed exploration of the configuration space based on historical datasets and the trend of the data.

Fig. 7 shows the throughput obtained during the tests of Table 1 compared with the throughput of the baseline. The results show an increased throughput and lower variability.

Using the estimations provided by PDU-RS, we were able to make informed decisions that resulted in an increase on reliability from 63% to 96% (compared with the base line tests), while running at 90% capability. The total runtime for the tests on Table 1 was 319.5 minutes with down time being 13.3 minutes. All of the down time measured was a result of a hardware interface issue and was not a result of equipment failure or overload.

VI. Conclusions

This paper presented a data-driven decision support system for controlling a plant for feedstock comminution. The paper further presented the implementation of the presented system and showed experimental results of using it in a real world PDU. The PDU-RS system provided a clear interface that summarized the information available in historical datasets. The extracted models allowed us to perform informed decisions that resulted in an increase in the system throughput and reliability. During the experimental evaluation, we did not experience any unexpected downtime thanks to the adequate selection of screen sizes and infeed rates based upon the estimations provided by the GP models. Using a linear function as the mean for the prior distribution allowed us to create models that provided estimations based upon the trend of the data when extrapolating for unexplored data spaces. The Gaussian kernels used for the covariance function of the GP provided a complementary functionality by modeling local nonlinearities. Modeling confidence was fundamental to validate the estimations of the GP and provided a visualization of the explored space. This was particularly useful for performing informed exploration of configurations that maximize throughput and reliability. Testing of the PDU using the PDU-RS showed a significant increase in capability over baseline operations with improved reliability.

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