

A Comprehensive Framework for the Modular Development of Condition Monitoring Systems for a Continuous Dry Granulation Line

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Abstract

The development of condition monitoring systems often follows a modular scheme where some systems are already embedded in certain equipment by their manufacturers, and some are distributed across various equipment and instruments. This work introduces a framework for guiding the modular development of monitoring systems and integrating them into a comprehensive model that can handle uncertainty of predictions from the constituent modules. Furthermore, this framework improves the robustness of the modular condition monitoring systems as it provides a methodology for maintaining quality assurance and preventing unnecessary shutdowns in the event of some modules going off-line due to condition-based maintenance interventions.

Keywords: Condition Monitoring, Probabilistic Programming, Modular, Machine Learning, Bayesian

1. Introduction

The challenges in modeling pharmaceutical powder processes, as outlined in Rogers and Ierapetritou (2014), has put an emphasis on the use of data-driven models as the basis for developing condition monitoring (CM) systems. While this approach offers a practical solution, as Webb and Romagnoli (2021) recently demonstrated for the Tennessee Eastman Process (TEP) case study, it ignores the modular nature of process control system development.

Since the data-driven models often require data spanning multiple unit operations in order to maximize the usage of process data, CM applications are likely to be on levels 1 and 2, which are distributed control systems in the process control implementation hierarchy introduced by Su *et al.* (2019). These modules are also likely to be focused on process faults, which differ from the CM modules at level 0, which are directly embedded into more advanced equipment. Because embedded modules are developed by the vendors, whose priority is on the safe and reliable operation of the equipment, they tend to focus on safety-related faults like electrical and mechanical faults.

All the aforementioned fault types need to be considered holistically, especially since they are likely correlated with each other. However, the varying levels at which these modules are installed in the process control implementation hierarchy, and the difference in their goals, create an integration challenge that needs to be addressed in order to have a safe and reliable operation of a continuous processing plant.

2. Condition Monitoring Framework Development

A natural framework for addressing this integration issue would be the probabilistic graphical modeling methodology, which is commonly used to implement hierarchical Bayesian models. As recently demonstrated by Radcliffe and Reklaitis (2021), this methodology is effective in systems where data is limited and there is significant uncertainty in the model parameters. Since this method is fundamentally based on modularity, where complex physical systems are constructed from simpler parts, it is sensible to utilize it for the CM module integration problem.

Under this methodology, the basic parts of the system are random variables with uncertain values, which are depicted as nodes in the graphical model. Conditional dependencies may be assigned based on expert knowledge on the system, and arcs can be drawn between one or more nodes to capture these relationships. Altogether, the nodes and the arcs comprising the probabilistic graphical model (PGM) form a compact representation of joint probability distributions where probability theory can be used to model the uncertainty in these variables and to make inferences on variables of interest.

2.1. A Probabilistic Condition Monitoring Model for Continuous Dry Granulation

The continuous dry granulation line of the Purdue University Pilot Plant comprises several unit operations that can blend pharmaceutical excipients and active pharmaceutical ingredients (API), granulate them, and then compress them into tablets using a rotary tablet press (see Figure 1). At the heart of this process is the granulation step, which takes place in an Alexanderwerk WP-120 roller compactor (RC). In the RC unit, the pharmaceutical blend is compacted into a ribbon, cut into flakes, and subsequently broken down into the desired granule size distribution in a classifier mill. For clarity in presenting basic concepts, the remaining discussion will focus on the RC.

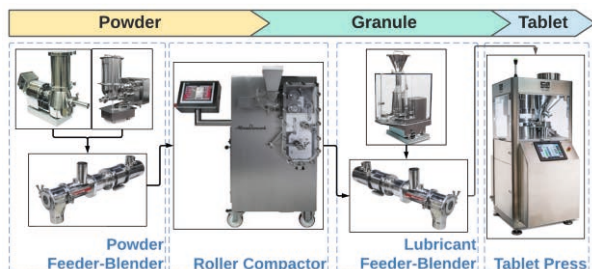


Figure 1. Dry granulation line at the Purdue University pilot plant.

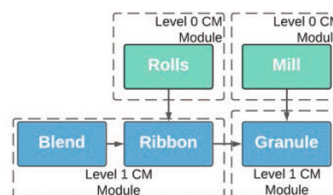


Figure 2. Roller compactor condition monitoring model.

A condition monitoring model can be constructed by considering two types of condition variables, the material condition and the equipment condition, and then forming appropriate relationships between them. For the RC, this model is shown in Figure 2. The roll and mill variables (green nodes) represent the condition of the respective roller compactor components. The WP-120 RC has a built-in condition monitoring system for each of these components, so these variables also represent “embedded” or “level 0” CM modules. The blend, ribbon, and granules variables do not have condition monitoring systems by default; so, these need to be developed as “distributed” or “level 1” CM modules that require the integration of additional PAT tools. Discussing the development of these modules is beyond the scope of the current paper, so they will be

assumed to provide uncertain values for their corresponding variables, as is the case for the embedded modules.

At this stage, the model in Figure 2 serves as a useful guideline for the modular development of CM modules that supports the complete observability of variables pertinent to Quality-by-Design (QBD) principles. Under QBD, the Critical-Quality-Attributes (CQA) targets of a unit operation should be achieved by controlling the Control Process Parameters (CPP) and the CQA of the preceding unit operation. For the RC model, the ability to control the CPP is represented by the condition of the equipment (i.e., the rolls and the mill), and the CQAs are represented by the condition of the material (i.e., blend, ribbon, and granules).

Each random variable in this graph, whether it is a material condition (blue node) or equipment condition (green node), can have discrete states: normal or a faulty state. With multiple variations possible for each faulty state, each node represents a categorical distribution, which assigns a probability for each possible state. For clarity, these distributions are depicted as probability tables that are linked to its corresponding node via broken lines in Figure 3. Moreover, the variables are assumed to take only two possible states, whereas in reality, they can have up to “N” number of states, depending on the number of faulty conditions that are recognized for each node.

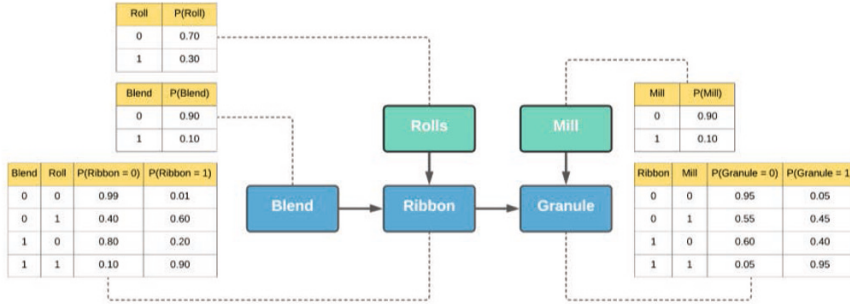


Figure 3. A probabilistic condition monitoring model for the roller compactor.

2.2. Probabilistic Programming and Inference

By the basic laws of probability, the entire graph represents the joint probability of all the condition monitoring variables per the following equation:

$$P(\text{Blend}, \text{Rolls}, \text{Ribbon}, \text{Mill}, \text{Granule}) = P(\text{Rolls})P(\text{Mill})P(\text{Blend})P(\text{Ribbon} | \text{Blend}, \text{Rolls})P(\text{Granule} | \text{Mill}, \text{Ribbon}) \quad (1)$$

With this model, interesting analysis tasks such as probabilistic inference can be performed. For example, given observations on the condition of the roll and the ribbon, e.g., both are at normal state so their values equal 0, it is possible to directly compute the posterior distribution of the condition of the blend using Bayes' Rule.

$$P(\text{Blend} | \text{Rolls} = 0, \text{Ribbon} = 0) = \frac{P(\text{Blend}, \text{Rolls}=0, \text{Ribbon}=0, \text{Mill}, \text{Granule})}{P(\text{Rolls}=0, \text{Ribbon}=0)} \quad (2)$$

$$\text{where: } P(\text{Rolls} = 0, \text{Ribbon} = 0) = \sum_{\text{Blend}, \text{Mill}, \text{Granule}} P(\text{Blend}, \text{Rolls} = 0, \text{Ribbon} = 0, \text{Mill}, \text{Granule}) \quad (3)$$

However, with modularity in mind, this model is expected to get bigger as adjacent unit operations along the manufacturing line are integrated. The increasing number of variables will slow down the exact inference computations to a point that makes it impractical for monitoring applications. To circumvent this, the graphical model can instead be encoded in a probabilistic programming framework like Infer.NET (Minka et al., 2018), where approximate inference tasks can be quickly performed via efficient message passing algorithms.

3. Results and Discussion

3.1. Parameter Learning

As demonstrated, a fully-defined model such as shown in Figure 3 can make useful predictions on variables based on observations from other variables. However, in practice, these parameters are not always initially available. Fortunately, the graphical modeling methodology can perform parameter learning by simply adding the parameters as variables in the graph, and then using the same approximate inference techniques to infer parameter values. Figure 4 shows the modified graph that addresses parameter learning; the yellow nodes represent the prior probabilities of the CM modules, and the block arrows depict message passing during the inference of the prior probabilities. In order for the message passing algorithms to remain computationally tractable as more modules are integrated, the probabilities of the parameter variables are assigned a Dirichlet distribution, which is a conjugate prior for a categorical distribution. This conjugacy ensures that the number of distribution parameters do not increase intractably during the implementation of the message passing algorithms. (Winn, Bishop, and Diethe 2015)

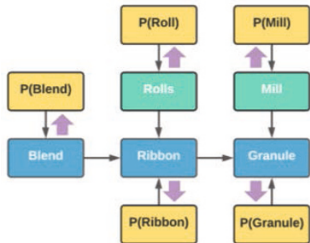


Figure 4. Parameter learning in a probabilistic graphical model.

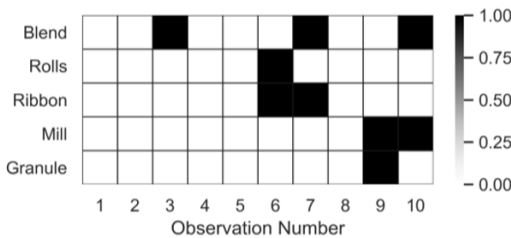


Figure 5. Dataset required for parameter learning (where all condition variables are observed).

Initially, the prior variables can be assigned either non-informative or weakly informative priors. Then, parameter learning can be performed on data acquired when all the CM modules are functional (see Figure 5), and message passing algorithms can be used to infer the posterior distributions of the parameter variables. As more data is collected, the inferred distribution of the parameter variables would be more “informed” and have less variance.

This can be observed from the results in Figure 6, which shows the inferred probabilities of the blend and mill condition. After just 100 observations, the comprehensive model was able to correctly infer the “true” probabilities of the model shown in Figure 3, which is from where the dataset was randomly sampled. Beyond this

number of observations, the mean of the inferred probability distributions barely changed, while the variance continued to decrease significantly.

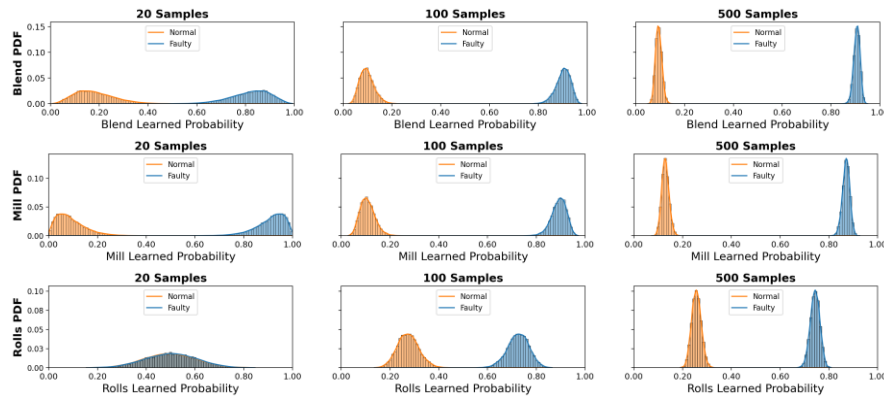


Figure 6. Learned probabilities for the blend, mill, and roll condition at varying sizes of training data.

3.2. Predictive Modeling

One of the main challenges in monitoring the CQA of the RC is the lack of current capability to measure the condition (e.g., flowability and tabletability) of the granules in real-time. Fortunately, the graphical modeling framework allows for the inference of the granule condition given observations from other CM modules. This scenario is shown in Figure 7, with the block arrows indicating message passing from observed variables that are not d-separated (Bishop 2006) from the granule variable. Results of this inference are shown in Figure 8, where based on observations from the surrounding CM modules, the probability of the granule condition changes correspondingly.

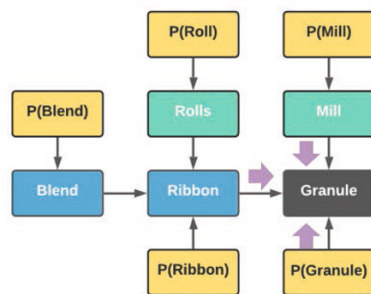


Figure 7. Granule Condition Inference Scheme

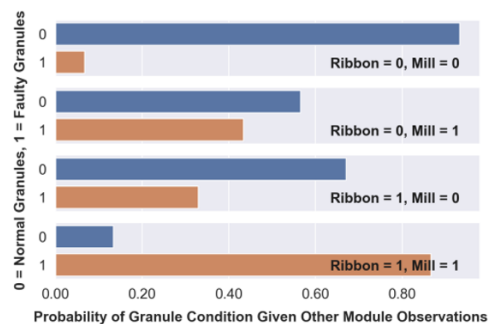


Figure 8. Inference Results on the Granule Condition

Throughout the operation of a continuous processing line, some CM modules might break down, rendering the condition of the actual material and equipment to be unobservable. For the RC example, the NIR sensor observing the ribbon could be undergoing maintenance because of fouling. While this temporary lack of observability could compromise quality assurance of the process, it should not be a reason for

shutting down. Using the message passing scheme shown in Figure 9, the condition of the granule could still be inferred from available CM modules such as the blend, rolls, and the mill condition monitoring modules. The results of these predictions are shown in Figure 10, for varying conditions of the blend, rolls, and the mill.

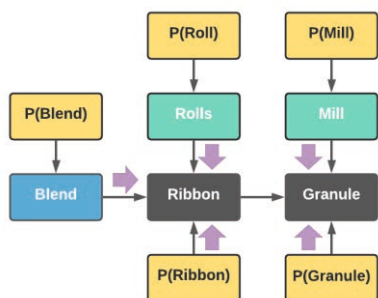


Figure 9. Inference Scheme with Multiple Unobserved Variables.

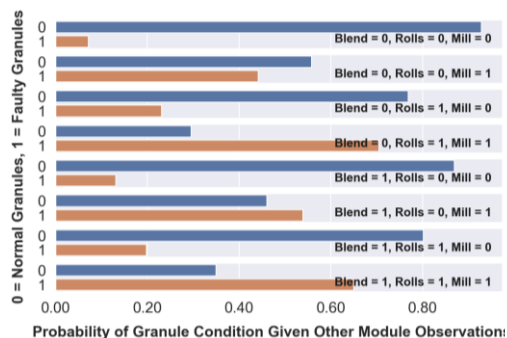


Figure 10. Inference Results on the Granule Condition with Unobserved Ribbon Condition.

4. Conclusions

A comprehensive condition monitoring model for a roller compactor was developed by first considering material and equipment condition variables that are involved, and then establishing logical relationships between them. The condition variables were assumed to be categorical variables with discrete states, and their relationships were encoded into a probabilistic programming framework. This framework was able to efficiently perform approximate inference to learn the parameters of the model, and most importantly, to infer the condition of other less-visible variables like the granule condition based on observations from other condition variables.

5. References

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