

Modeling and Calibration of Combine, Impact Plate, Yield Sensors

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ABSTRACT

An effort was undertaken to capture the relationship between the output of mass flow sensors and the input rate of mass flow for harvesting combines with yield monitors. Different types of models were considered that characterize this relationship and that can be applied to a variety of mass flow sensor technologies. Issues such as implementation during harvesting and calibration of these sensors and models were explored. Additionally, an example of such a model and its validation against experimental data was examined. For small-scale laboratory experiments, the model was shown to closely capture the general trend of the data as well as to yield reasonable estimates of the mass flowing through the system based on the sensor output. For large-scale experiments, the model was able to be fitted to the experimental data, and to estimate mass flow rate with relatively low errors across a variety of operating conditions.

INTRODUCTION

Farmers need to account for the amount of grain being harvested in order to make better decisions in the application of different farming practices; to achieve improved and more reliable yield; to better estimate the monetary value of their harvest; to allow yield comparisons between different crop varieties and treatments within a field; to provide a traceable record of yield from each field; and to make yield maps. To this end, mass flow sensing systems must be both accurate and precise as inaccuracy or great variability in the measured output may lead to incorrect conclusions and decisions

regarding farming methods and associated financial estimates. Furthermore, such systems need to be easy to use and maintain so as to ensure sustained reliability across their lifetime. Broad adoption of reliable yield sensing systems provides a competitive advantage and reduces financial risks associated with uncertainty in production output.

A variety of types of mass flow sensors have been proposed in the literature and/or implemented in actual yield sensing systems. These can be classified by the underlying principle of measurement, namely, sensors which characterize the volume of grain through measurements of the bulk; sensors whose measurement output relies on direct contact methods in which individual grains interact with a specific mechanical component; and sensors that rely on indirect measurement principles, in which a secondary effect of the grain flow is used to quantify the yield. Examples include paddlewheels [1], optical devices mounted in the clean grain elevator [2,3], plate impact sensors [4], torque sensors mounted on the elevator paddles [4], torque sensors mounted on the clean grain elevator drive shaft [5], diaphragm impact sensors [6], pivoted-auger-fed devices [7], scales for weighing of the clean grain auger [8], capacitive sensors [9], ultrasonic sensors [9], and sensors relying on x-ray measurement principles [10].

As with any sensor, it falls upon the designer of the sensing system to establish a computable relationship between the output of the sensor and the desired, not directly measurable, physical quantity, here the rate of mass flow. We refer to such a relationship as a *model*. Several strategies exist to

provide a model of the relationship between the output of the sensor and the rate of mass flow. These can be grouped into three types, namely, *data-based*, *empirical*, and *physical* models. Data-based models consist of look-up tables, indexed by the inputs and outputs of the system and sensor, coupled with suitable interpolation routines. Empirical models provide the relationship between sensor output and mass flow rate in the form of an algorithm (function) explicitly parameterized by dimensionless combinations of machine and operational parameters, which captures and aligns well with experimentally observed trends. Finally, physical models quantify the desired relationship in terms of an algorithm whose component parts are arrived at through an analysis of the fundamental machine and grain properties and their dynamics.

Models are useful only as long as they are (and can be) calibrated to the actual conditions of operation. Common challenges to reliable and consistent calibration are variability across grain varieties, changing grain conditions (e.g., surface and body moisture), and aging of system components (e.g., elevator paddles). These challenges are further magnified in that combine operators not only need to recognize that such changes are taking place, but must also be able to re-calibrate their systems appropriately. If calibration is performed by the equipment manufacturer in a factory setting, the burden of calibration is relieved from the combine operator. On the other hand, there may be limited value to such factory calibration if new harvesting conditions are encountered during operation. If calibration is performed by the combine operator, better accuracy and flexibility can be achieved to match the specific conditions at which harvesting is taking place, but at the cost of additional time and effort.

In light of the above observations and the operational needs of combine operators, mass flow sensing systems should have the ability to estimate mass flow rates in the range of 0-25 kg/s with errors below 5%, and provide flow rate estimates at a sufficiently high sampling frequency so as to provide adequate spatial resolution across a field (i.e. on the order of 1 Hz). A robust system that is relatively insensitive, or adaptable, to changes in crop and machine conditions is clearly beneficial as it may reduce the need for re-calibration. Finally, calibration procedures should be straightforward (and cheap) to implement to ensure that combine operators will willingly perform such actions when required.

In this paper, we document an effort to arrive at a computable relationship between the output of an impact plate mass flow sensor and the input rate of mass flow so as to achieve accurate and reliable mass flow rate estimation. The discussion is illustrated through an example physical model that provides this relationship in terms of a computable algorithm for predicting the force applied to the impact plate in terms of mass flow rate, machine and grain properties, and dynamic interactions between the grain and the machine

environment. Additionally, experimental data is used to validate this model and to explore the ease with which it may be reliably calibrated.

IMPACT PLATE SENSORS

Impact plate sensors rely on direct mechanical contact between grains and an element in the machine environment to provide a sensor output that is representative of the mass flow rate. An example of such a sensor is shown in Fig. 1. Grain enters the clean grain elevator via an auger and is deposited onto elevator paddles. A rotating sprocket cycles the elevator paddles, causing grain to be propelled towards the impact plate as the paddles move in a circular fashion about the sprocket. The output of the sensor is a voltage that is proportional to the deflection of the impact plate and related to the momentum imparted to (and average force applied to) the impact plate. Knowledge of this momentum is then used to characterize the mass flow rate.

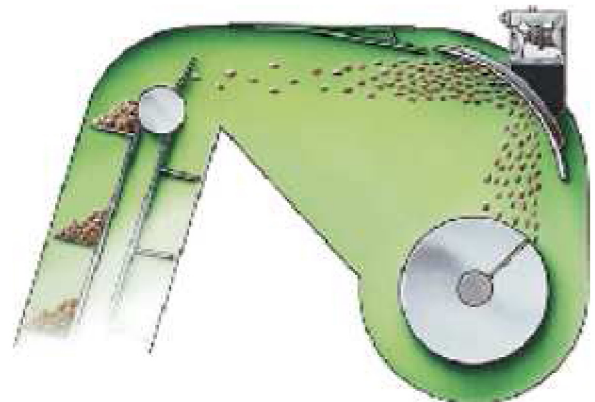


Figure 1. Realization of a mass flow sensing system. Grain deposited onto elevator paddles is cycled by a rotating sprocket. The grain is propelled away from the elevator system by the rotating elevator paddles, and subsequently bounces against an impact plate sensor. A voltage representative of the deflection of the plate is suitably scaled and integrated to quantify the exchange of momentum between the grain flow and the plate. (This figure is reproduced with permission of Deere and Co.)

MODEL DEVELOPMENT

The fundamental objective of the mass-flow-sensing system is to provide accurate yield estimates during real-time operation of harvesting combines under a variety of operating conditions. To achieve this objective it is necessary to arrive at a relationship between the input(s) and the output(s), which can be reliably interrogated to estimate inputs given measured outputs. In this section, we discuss three different types of models that can be used for this purpose: data-based models, empirical models, and physical models.

DATA-BASED MODELS

Data-based models are based on numerical look-up tables, indexed by a collection of experimentally collected values of inputs and containing the corresponding experimentally collected values of the outputs. Such models are particularly useful if the output is (within measurement uncertainty) a unique function of the input and vice versa. Prediction of the output is then achieved by interpolating the content of the table elements whose indices agree most closely with the given input conditions. Similarly, estimation of the input is achieved by interpolating the indices of the table elements whose content agree most closely with the given output conditions.

The development of data-based models is accomplished through an act of calibration, in which (possibly vast quantities of) data is experimentally collected to generate an approximate covering of typical operating conditions. Given the uncertainty in the collected experimental data and the difficulty in controlling for operating conditions outside of the measurable inputs, data-based models would typically only provide reliable operation in severely constrained applications.

EMPIRICAL MODELS

Empirical models seek to experimentally identify functional relationships between dimensionless combinations of input and output variables. For example, in the case of the impact-plate mass-flow sensor, the ratio

$$\alpha = \frac{\langle m \rangle V}{\tau \langle F \rangle} \quad (1)$$

is a dimensionless combination of the average mass $\langle m \rangle$ that flows past a given cross-sectional area over some characteristic time τ , the average force $\langle F \rangle$ on the impact plate during this characteristic time, and the translational velocity V of the elevator paddles during their vertical ascent. An empirical model based solely on this dimensionless quantity is then a functional relationship of the form

$$f(\alpha) = 0, \quad (2)$$

where f is some arbitrary (dimensionless) function of a single variable. This constitutes a (nonlinear) equation in α with (typically, at best) isolated solutions

$$\alpha = \alpha_0 \Rightarrow \dot{m} \stackrel{\text{def}}{=} \frac{\langle m \rangle}{\tau} = \alpha_0 \frac{\langle F \rangle}{V} \quad (3)$$

for some dimensionless constant α_0 . Calibration of this model simply amounts to estimating α_0 from a large statistical

sample of numerical values for α , given otherwise constant conditions.

Reliance on the single dimensionless quantity α amounts to the modeling assumption that the value of α_0 is independent of $\langle m \rangle$, V , τ , and $\langle F \rangle$ and only a function of other, not controlled for, operating parameters that describe the experimental apparatus. The extent to which this can be reliably assumed can be statistically evaluated by exploring the distribution of values of α for otherwise constant conditions. Biasing behavior as a function of any one of the four fundamental quantities $\langle m \rangle$, V , τ , and $\langle F \rangle$ then suggests a need to enlarge the model to (at least) one additional dimensionless quantity.

Consider, for example, the dimensionless combination

$$\beta = \frac{\eta w l^2 V \Omega}{\langle F \rangle} \quad (4)$$

of the grain volume density η , the width of the elevator paddle w , the length of the elevator paddle l , the translational velocity V of the elevator paddle during the vertical ascent, the angular speed of the sprocket Ω , and the average force $\langle F \rangle$ on the impact plate during the characteristic time τ . An empirical model based on α and β is then a functional relationship of the form

$$f(\alpha, \beta) = 0, \quad (5)$$

where f is some arbitrary (dimensionless) function of two variables. This constitutes a (nonlinear) equation in α as a function of β with (typically) a continuum of solutions. Suppose, for example, that

$$f : (x, y) \mapsto xy - c_1 y - c_2, \quad (6)$$

in which case

$$\alpha\beta - c_1\beta - c_2 = 0 \Rightarrow \dot{m} = c_1 \frac{\langle F \rangle}{V} + c_2 \frac{1}{\eta w l^2 \Omega} \left(\frac{\langle F \rangle}{V} \right)^2 \quad (7)$$

for some dimensionless constants c_1 and c_2 . Calibration of this model amounts to estimating c_1 and c_2 by fitting the straight line $c_1 + \beta c_2$ to the product $\alpha\beta$ using a large statistical sample of numerical values for α and β given otherwise constant conditions.

The systematic reliance on dimensionless quantities allows one to enlarge the model complexity in successive steps.