# IMPROVING IRON MAKING PROCESSES WITH MULTIVARIABLE PREDICTIVE CONTROL TECHNOLOGY[1]

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## Abstract

High performance control of an interactive process such as a sinter plant relies on ability to: honor safety and operational constraints; reduce the standard deviations of variables that need to be controlled (e.g. product quantity, quality); de-bottlenecking the process; and, maximize profitability or lower cost (e.g. energy savings, improve hot metal content). These objectives may be prioritized in this order, but can vary and are very difficult to achieve optimally through conventional control. Multivariable predictive control is a control technique that has been successfully applied throughout the hydrocarbon processing industries to provide high performance control since the early 1970's. This technique is now starting to be used within the metals and mining industries with similar results. A multivariable predictive controller solution, along with its extensive inferential sensor and built-in optimizer, provides online closed loop control and optimization for many interactive metal and mining processes to lower the energy cost, increase throughput, and optimize product quality and yield. This paper, through an example for sinter plant process control, discusses how the technology can applied to the high energy intensity process of Iron and steel making.

**Key words:** Multivariable control; Predictive control; Sintering; Pelletizing.

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## INTRODUCTION

The advancement of low cost computing technology in the last two decades has allowed the proliferation of multivariable model-based control techniques in many process industries. These applications have proven to provide huge benefits through the stabilization of the operation and optimization of the process. Multivariable Predictive Control (MPC) is one such technique that allows the control of an entire process as a single entity rather than as a collection of isolated control loops. In this way the MPC Acting like a high performance managing a number of single-loop controllers consistently, the MPC simultaneously handles large numbers of process variables and understands future process dynamics thus ensuring that process constraints are not violated.

Payback periods of MPC implementation from less than one month to a typical six months have been reported in many petrochemical process areas, lately the technology has been applied in various process areas of metals and mining industry and similar benefits[1,2,3] were reported. Most importantly, the successes of these MPC implementations are demonstrating high sustainability where, in many cases, service factors of over 95% are achieved.

With higher input cost and tighten environmental requirements, integrated Iron and Steel producers are placing stronger focus in improving the process control of those production units where a high energy consumption is required. In either the Oxygen making route or Direct Reduction route, the high energy intensity production units reside mostly in the ore agglomeration, reductant preparation, and iron making areas. These process areas (such as the pelletizer, sintering bed, coke oven, Blast Furnace hot stoves, Direct Reduction unit, air separation unit) require significant amounts of fuel. In addition these units generate significant amounts of waste heat or gases that can be re-captured and re-cycled. Small percentage savings of the energy input or energy recovery of these process areas means millions of dollars per year to the plant. Multivariable predictive control can provide the means to achieve these benefits.

## GENERAL CONCEPTS OF MULTIVARIABLE PREDICTIVE CONTROL

Current Multivariable Predictive Control software has its roots in a set of model-based control algorithms proposed and implemented within the process industry in the late 1970s[4,5]. Subsequently, many important developments have flourished which have resulted in currently available robust multivariable controllers that can handle large numbers of input and output process variables, are able to operate with constraints, can deal with long dead-times, and incorporate optimization capabilities. The technology advancements have provided tools with easy to use model identification for project implementation and future modification together with intuitive Man-machine interfaces for operator acceptance. Improvements in robustness of the control such that any gradual change of the process, equipment, or feedstock can be auto-adapted[6] have allowed the modern MPC implementations to run with very high service factors.

The kernel of a MPC is a dynamic interaction model (identified on-line through a set of software tools) of the process. This computing model runs in parallel with the real plant and is subject to the same measurement inputs as the plant. The model is used to compute a predicted output trajectory over a certain number of future time horizons at each sample point. An optimization problem is then solved to minimize the deviation of this predicted output from a desired trajectory into the future. The decision variables are computed control moves that will output to the plant, and in the meantime feedback to the model. These steps are repeated to allow continuous control of the process. Process variable constraints are included explicitly in the control calculation when the optimization step is set up such that the control moves are subject to the satisfaction of these constraints.

The ultimate success of MPC (or any control) is highly dependant upon the availability of accurate online measurements. Many critical process variables, such as ore characteristics and product quality, are not economically and/or timely being measured on-line as feed-forward or feed-back information for control. However current computing technology, in process control, resolves this critical issue through the use of inferential modeling techniques such as multivariate statistics, neural networks, or empirical models. These techniques provide the soft-sensing of these missing process variables, and can easily be coupled to a MPC for closed loop control of the process.

Figure 1 shows a block diagram of a modern Multivariable Predictive Controller (Profit Controller from Honeywell) with an inferential module to provide the soft sensing of certain process variables.

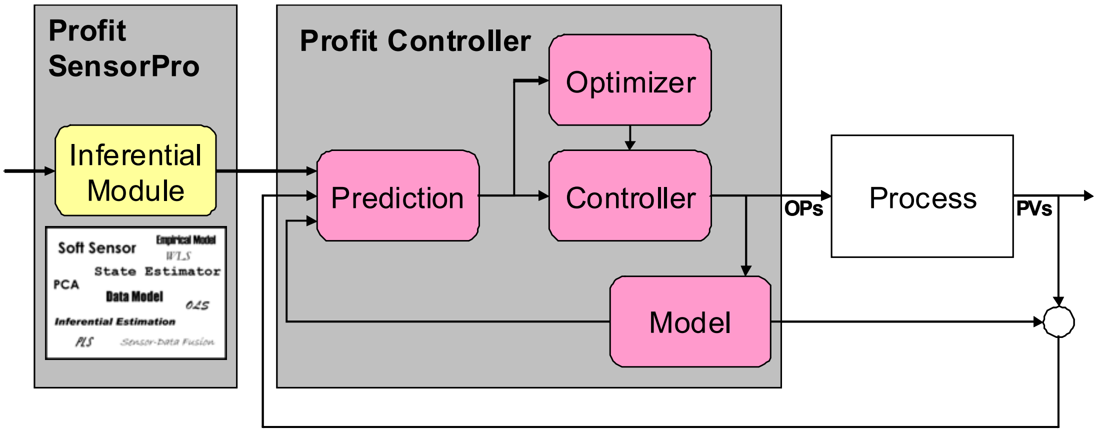


**Figure 1.** Block diagram of Honeywell's Profit Controller with Profit SensorPro

## SINTERING PLANT CONTROL EXAMPLE

Agglomerated ores suitable to be fed into a Blast Furnace need not only the right chemical composition to ensure quality hot metal production, but the feedstock also requires to be tightly controlled for its physical properties such as size, porosity, and compressible strength. This provides for the gas permeability necessary inside today's increasingly larger volume blast furnaces. The iron ore agglomeration process, either sintering or pelletizing, is one of the very key process steps in stabilizing the operation of the Blast Furnace.

Sintering is primarily achieved by the forced combustion of a layer of iron ore mixed with a controlled percentage of fine coke, called coke breeze. This causes partial melting of the individual iron particles and fusing them together. Sintered Ore product is typically fed directly to the Blast Furnace via a conveyor belt. A typical sintering process operation consists of feed mix preparation, drum mixing, ignition furnace, sinter travelling bed, crushing, screening, and cooling is illustrated in Figure 2.

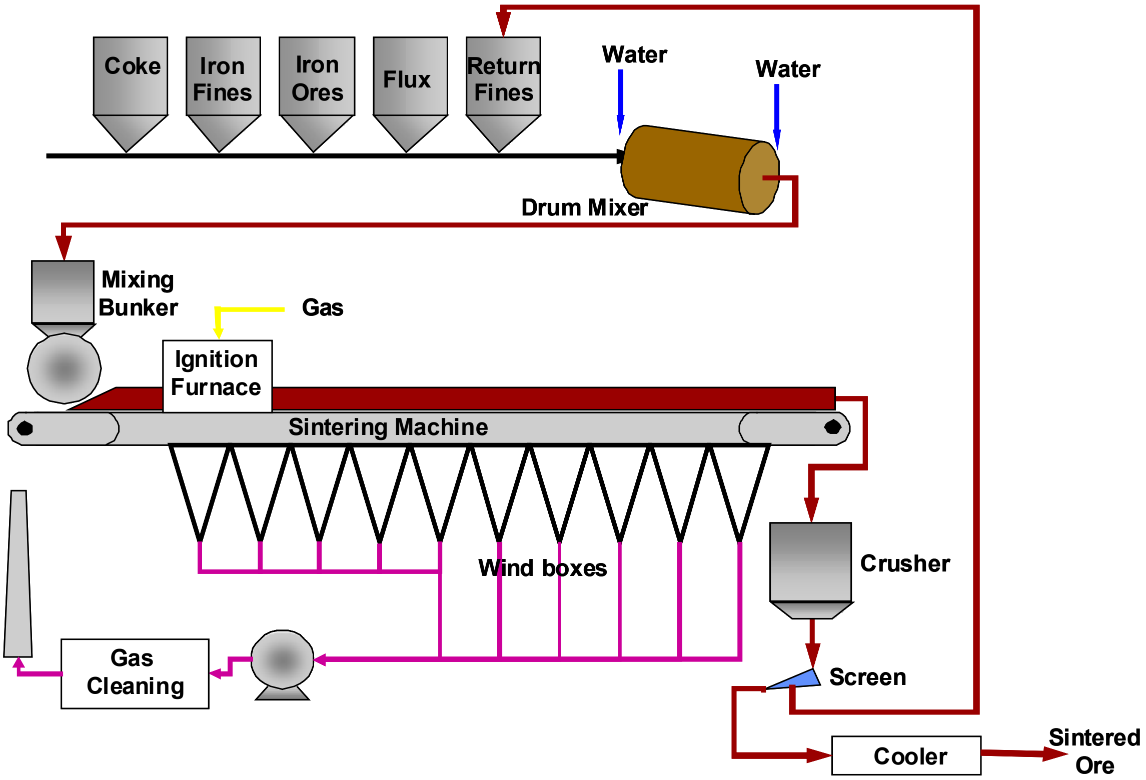


**Figure 2.** Typical Sintering Process Flow Diagram

Pre-mixed sintering materials coming out from the drum mixer is fed onto the travelling belt. The travelling belt then transports the sinter mix as a bed to an ignition hood which ignites the coke breeze in the upper surface of the sinter bed. Combustion lower down in the mix is maintained by air flowing through the bed with air suction from the wind-boxes.

The objectives of this process are to achieve the conversion of fine ores into clinker-like aggregate with a suitable size, and composition for blast furnace feed. Further this must be achieved as fast as possible using the least amount of energy whilst maintaining all process constraints (such as sinter exit temperature). This is a highly interactive process with a number of unique challenges:

(1) Feed mix variations due to the varying ore bodies nature, and also quite often when switching of ores suppliers or mining locations;
(2) Contrasting time delays of the sintering process with less than 1 minute in the ignition and flue gas cycle, and over 30 minutes for the solids traveling on the sintering bed;
(3) Lacking of accurate online measurement to measure many feed and product variables such as hardness, basicity, feed moisture, and ore porosity.

An accurate feedstock planning tool can predetermine the necessary blend recipe of the feedstock so that chemical properties of the end-product are met and optimal coke breeze percentage is calculated. However, high performance sintering production also requires a superb management of the sintering bed from material charging to discharging. The sector gate and actuator of the feeding bunker needs to be controlled to achieve a desirable profile of the sinter distribution onto the bed. The burners require firing at optimal air/fuel ratio to ignite the coke breeze, and the sinter bed grating speed should be controlled at its highest possible speed while ensuring complete combustion of the sinter on the bed before discharging. Traditionally, the feed preparation blending, the drum mixing, the feeding bunker, the ignition furnace burner, the sinter bed speed, and the windbox suction are controlled by isolated control loops. But because all these variables interact it is very difficult to achieve optimal control using conventional control.

Some of these control problems could be overcome through cascading into feedforward and/or feedback control schemes with appropriate decoupling. However variability of feed moisture, percentage of reject ores, iron fine compositions, coke breeze caloric value and compositions, ignition furnace fuel pressure and caloric value, flue gas suction pressure, ambient humidity will still present challenges for even the best operators to juggle between the interactive, and sometimes conflicting, control objectives. Multivariable predictive control can simultaneously control all these variables whilst maintaining operational constraints and optimize for throughput and energy.

## POSSIBLE MULTIVARIBLE PREDICTIVE CONTROL SOLUTION

To discuss how MPC can solve the sinter control problem it is necessary to understand some of the terminology associated with MPC. Process variables are classified into:

(1) Controlled variables (CV's) – the variables that the MPC controller is designed to "control" (within a range or to a setpoint),
(2) Manipulated Variables (MV's) – the values that can be moved by the MPC controller within a range to control the CV's,
(3) Disturbance Variables (DV's) - these variables impact the process but the controller is not allowed to move the value.

In the sintering process example, depending on the process flow, instruments installed, and boundaries of controller, CV's will be such as the windbox temperature of the sinter bed, the sinter bed depth, sinter product mechanical strength, MV's will be such as the feeding bunker flow rate, traveling grate speed, suction fan speed, damper position, and DV's will be such as coke breeze ratio, return fine percentage, ignition fuel pressure, and fuel caloric value.

Figure 3 illustrates how these variables relate to the MPC, and typical setup of MPC cascading to the standalone single loop control for fall-back manual operation.

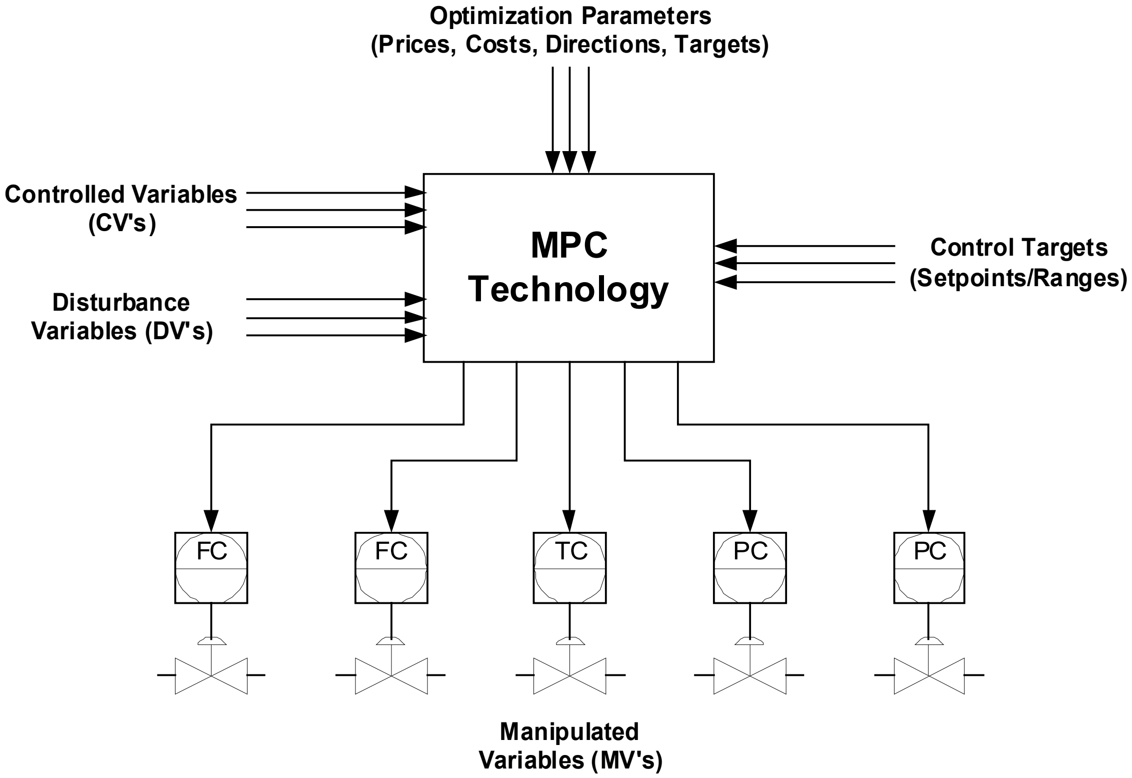


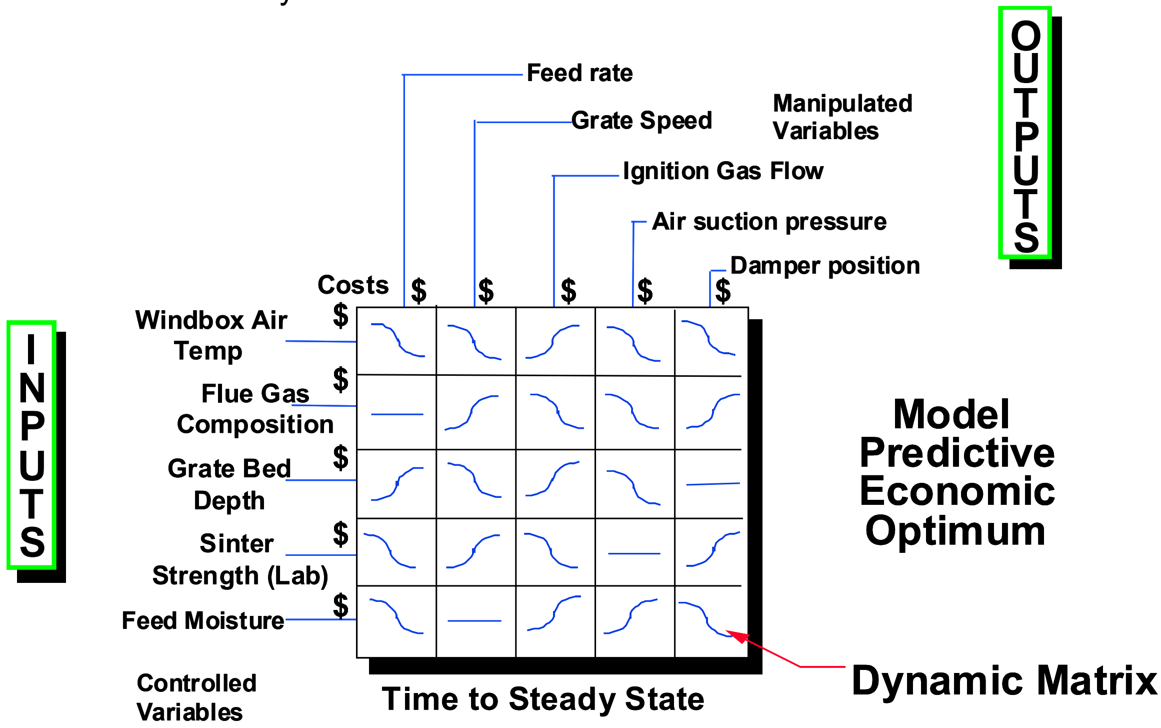
**Figure 3,** MPC Variables and typical cascading set-up with single loop controllers

## IMPLEMENTATION METHODOLOGY

Modern MPC technology provides many convenient tools for the user to define the controller, identify the model, validate the effectiveness, and commission for online closed loop control. A possible MPC project implementation for a sintering process will involve the following steps:

1. **Controller definition**
   Although MPC nowadays can easily handle very large matrix of variables in a single controller, it is often a project decision to determine the choice of one large controller or splitting it into multiple smaller ones. A process consideration must be given to the ease of implementation, interactions between the process variables, impact when a model is out of services, and more importantly the intuitiveness for the operators.
   A preferable configuration for the sintering process is to adopt two multivariable controllers: (1) feed preparation blending control, and (2) sintering bed process from charging to discharging including the windbox suction and flue gas waste heat recovery. Modern MPC technology, such as Honeywell’s ProfitOptimizer, provides features where multiple MPC’s can be connected to each other and economic objectives can be globally observed.
   The matrix including CV’s, MV’s and DV’s of each controller will be defined in this stage.
2. **System Identification**
   A process called step testing is necessary to find out the dynamic response of the inputs and outputs, and through the response the MPC model is identified. By moving one of the inputs and keeping the other inputs constant, the dynamic of the outputs can be observed through this step test process.

Figure 4 shows an example model matrix and dynamic responses of the inputs and outputs. Software tools, such as the Honeywell Profit Design Studio, are available for the system identification and computation of the response equations with the best fitted parameters.
In the cases where inferential technology (for unmeasured properties) is required these can be constructed from historical plant data using modern tools such as Honeywell's ProfitSensor Pro.



**Disturbance Variables: Feed Moisture, Fuel/Coke caloric value, Return fine quality**

**Figure 4,** Conceptual Input-Output Model: Results of System Identification of Sintering plant

### 3. Controller commissioning

The model derived through the model identification is then hosted on a computer connected to the control system. The MPC is set up as a multivariable cascade controller connected to the control loops of the manipulated variables under an Auto/Manual selection. Man-machine interfaces are provided to the operator and maintenance staff for the operation, troubleshooting, and maintenance of the controller.
A common practice during this commissioning phase is to put the controller in a read only mode, i.e. the controller is connected online but not sending its setpoints to the single loop controllers. Once the model is validated and the operation team is comfortable with this new way of controlling, the controller can be put into online closed loop operation.

## ESTIMATED BENEFITS

Each sintering process has its own control issues and objectives. Some are throughput limited, some do not have variable frequency drive on the suction fan, some have windboxes that could cause rim zone effect, some have limited instruments in measuring moisture content, and some have many types of ore with different optimum set points for each type. Because each circuit has different objectives, the MPC benefits will vary from site to site.

To generalize, it is typical to realize a throughput increase of 1% or more by applying multivariable predictive control. These throughputs can result from reducing the variations between operation teams, stabilizing sinter quality and hence lowering reject, pushing closer to the maximum constraint on throughput, avoiding downtime through stable controls, or a combination of all of these. In additional, energy savings of 2 to 10% can be achieved through lowering ignition fuel burn and optimization of coke breeze and tightening control of windbox suction power and cooling. Because of the stability of control there will also be a lowering of greenhouse gas emissions. These benefits can provide millions of dollars worth of additional profit per year for a typical operation.

## CONCLUSIONS

Advanced process control techniques such as multivariable predictive control can show improvements and pay for itself in a short period when compared to a simple PID or manual operation. The iron and steel industry should look at the experience of other industries in evaluating the life cycle cost and the future potential of systematic expansion to plant-wide optimization offered by MPC techniques. The latest MPC technologies allow easy or automatic identification of the model making implementation straightforward. The increased robustness of the controller coupled to its feedback trim ensures that the MPC controller will be available with a high service factor even with feedstock changes and equipment condition degradation.

MPC technology has been demonstrated to be applicable to metals and mining processing units with many successful applications. Typically, providing benefits of over 1% improvement in the throughput of usable product. This may represent millions of dollars per year increase in revenue for a typical process unit.

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