

NRC Publications Archive Archives des publications du CNRC

Agent-based control of manufacturing processes

Albadawi, Zahir; Boulet, Benoit; DiRaddo, Robert; Girard, Patrick; Rail, Alexandre; Thomson, Vincent

This publication could be one of several versions: author's original, accepted manuscript or the publisher's version. / La version de cette publication peut être l'une des suivantes : la version prépublication de l'auteur, la version acceptée du manuscrit ou la version de l'éditeur.

For the publisher's version, please access the DOI link below./ Pour consulter la version de l'éditeur, utilisez le lien DOI ci-dessous.

Publisher's version / Version de l'éditeur:

https://doi.org/10.1504/IJMR.2006.012256 International Journal of Manufacturing Research, 1, 4, pp. 466-481, 2006-08-01

NRC Publications Record / Notice d'Archives des publications de CNRC:

https://nrc-publications.canada.ca/eng/view/object/?id=70899707-98d9-43a3-9709-4b31612c0cd4 https://publications-cnrc.canada.ca/fra/voir/objet/?id=70899707-98d9-43a3-9709-4b31612c0cd4

Access and use of this website and the material on it are subject to the Terms and Conditions set forth at <u>https://nrc-publications.canada.ca/eng/copyright</u> READ THESE TERMS AND CONDITIONS CAREFULLY BEFORE USING THIS WEBSITE.

L'accès à ce site Web et l'utilisation de son contenu sont assujettis aux conditions présentées dans le site https://publications-cnrc.canada.ca/fra/droits LISEZ CES CONDITIONS ATTENTIVEMENT AVANT D'UTILISER CE SITE WEB.

Questions? Contact the NRC Publications Archive team at PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca. If you wish to email the authors directly, please see the first page of the publication for their contact information.

Vous avez des questions? Nous pouvons vous aider. Pour communiquer directement avec un auteur, consultez la première page de la revue dans laquelle son article a été publié afin de trouver ses coordonnées. Si vous n'arrivez pas à les repérer, communiquez avec nous à PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca.





Agent-based control of manufacturing processes

Zahir Albadawi

Department of Mechanical Engineering, McGill University, Montreal, QC, Canada, H3A 2K6 E-mail: zahir.albadawi@mcgill.ca

Benoit Boulet

Department of Electrical Engineering, McGill University, Montreal, QC, Canada, H3A 2A7 E-mail: benoit.boulet@mcgill.ca

Robert DiRaddo and Patrick Girard

Industrial Materials Institute, National Research Council Boucherville, QC, Canada, J4B 6Y4 E-mail: robert.diraddo@nrc.ca E-mail: patrick.girard@nrc.ca

Alexandre Rail

Domfer Metal Powders, Lasalle QC, Canada, H8N 2S3 E-mail: arail@domfer.com

Vincent Thomson*

Department of Mechanical Engineering, McGill University, Montreal, QC, Canada, H3A 2K6 E-mail: vincent.thomson@mcgill.ca *Corresponding author

Abstract: Modern manufacturing systems deal with highly dynamic and complex processes, and need to adapt to rapid changes in manufacturing environments. These requirements can be met by model-based control that greatly improves process adaptiveness by integrating process phenomena knowledge with advanced simulation tools. Intelligent agent-based technologies provide a flexible platform for the implementation of model-based control. Two model-based control systems were implemented using an agent-based architecture: a linear, tuneable model for the plastic thermoforming process, and a non-linear, mathematical and rule-based model for the metal powder grinding process. Resulting advantages and improvements in performance, adaptiveness and productivity are highlighted.

Keywords: adaptivity; agent; architecture; ball mill grinding; control; diagnostics; error recovery; flexibility; model-based control; thermoforming.

Reference to this paper should be made as follows: Albadawi, Z., Boulet, B., DiRaddo, R., Girard, P., Rail, A. and Thomson, V. (2006) 'Agent-based control of manufacturing processes', *Int. J. Manufacturing Research*, Vol. 1, No. 4, pp.466–481.

Biographical notes: Zahir Albadawi received his BS (1993) in Mechanical Engineering from the University of Tehran, Iran, and his MS (2003) from Concordia University, Montreal. He is currently a PhD student in the Department of Mechanical Engineering, McGill University. His research interests focus on process design and control for manufacturing processes. His PhD research is on agent-based architecture for model-based control.

Benoit Boulet is a William Dawson Scholar and an Associate Professor in the Department of Electrical and Computer Engineering at McGill University. He is Director of the Industrial Automation Laboratory within the Centre for Intelligent Machines. Prof. Boulet has a BE Université Laval (1990), a ME McGill University (1992) and a PhD University of Toronto (1996) in Electrical Engineering. His research is concerned with finding practical solutions to automation and control problems in the areas of robust industrial process control, robust vehicle control and manufacturing execution systems.

Robert DiRaddo obtained his Bachelor, Masters and PhD degrees in Engineering at McGill University. After graduating, he worked for two international resin manufacturers for three years. He has worked at the Industrial Material Institute of the National Research Council of Canada for the past 15 years. He is group leader for software development for blow-moulding and thermoforming applications. Robert operates two successful consortia for software development in blow moulding and thermoforming. His group is now developing technologies for the medical sector.

Patrick Girard obtained his Bachelor degree in Engineering from École Nationale Supérieure d'Arts et Métiers (France) and then his MSc from École Polytechnique (Montréal). He is a Research Officer in the Intelligent Forming Technologies group of the Industrial Materials Institute, National Research Council of Canada. His expertise includes modelling of plastic forming processes, control systems for the plastic blow and thermoforming processes and technology transfer from research laboratory to industry.

Alexandre Rail is Production Manager at Domfer Metal Powders Ltd. He obtained his PhD in Mechanical Engineering at McGill University in 2006. He has been involved in the development of manufacturing systems for the past 8 years. His present research interests are operations management, model-based control for grinding and metallurgical processes, production design and market development. Through his work and research, he participates in product development, productivity and quality optimisation, computer systems and automation. In addition, he collaborates on industrial projects with students.

Vincent Thomson is the Werner Graupe Professor of Manufacturing Automation at McGill University. He is also the co-Director of the Master in Manufacturing Management (MMM). He has been involved in manufacturing and information technology research for the past 25 years at McGill University and the National Research Council (Canada). His present research interests are model-based control, fabrication techniques and information exchange and process design issues for engineering and manufacturing. He participates in about 20 industrial improvement projects each year.

1 Introduction

In today's manufacturing industry, production processes can only be profitable if they are highly optimised for maximum quality and minimal cycle times. Control architectures for real time control of manufacturing processes commonly need to satisfy requirements such as reliability, robustness, interoperability and reconfigurability. The next generation manufacturing systems require system architectures that adapt dynamically to environments often plagued by uncertain information, background noise and non-linear processes. This uncertainty results from incomplete process specifications for new products and dynamically changing processing and material parameters.

Traditional, centralised architectures based on PID or H-infinity control mechanisms have been found to be insufficiently flexible to respond well to these types of highly dynamic processes. Model-based control built on the integration of process know-how and simulation tools can address these ever increasing control requirements. Such a model-based control system uses an overall synthetic process model that relies on submodels of various process phenomena. These sub-models represent various physical features of the process, where these features often have different time scales. As a result, the control strategy is usually highly complex.

Agent technology allows the implementation of distributed, highly adaptive, intelligent manufacturing systems. Multi-agent systems also allow decentralisation of control, which reduces complexity and increases adaptiveness; they can cope with multiple models that are very different in size and operate on dissimilar time scales. These features make them especially suited for building model-based control systems.

The remainder of this paper is structured as follows. Section 2 briefly defines the requirements for an adaptive control system, and how agent-based technology can satisfy these requirements. In Section 3, an agent-based architecture that supports model-based control of manufacturing processes is described. Then, two examples of agent-based systems are given. First, Section 4 describes the thermoforming process, and model-based control for thermoforming is detailed in Section 5. The metal powder grinding process is explained in Section 6, and model-based control for metal powder grinding is given in Section 7. Results showing the improvements with agent-based control are given in Section 8. Section 9 discusses the key features of the agent-based architecture and its successes in the two applications. Lastly, Section 10 presents some conclusions with respect to the performance of the agent-based architecture.

2 Model-based control using agent-based technology

Model-based control provides the framework in which required control parameters are calculated by using state variables in mathematical and/or heuristic models of the process. It can cope with complex processes, where each process is modelled as one general model and/or several sub-models. Given enough knowledge of the process physics, simulations can accurately predict the physical phenomena to be controlled. The required complexity can be quite high, since the process models need to contend with non-linear phenomena and coupled process parameters.

Model-based control permits greater adaptability by having a deep knowledge of the phenomena involved in a process and its surrounding environment. Process models can achieve great precision by being able to evaluate certain required state variables that are not measurable during the process. If models accurately represent process phenomena, model-based systems can control highly dynamic processes incorporating multiple, coupled sub-processes. An example for thermoforming is described in Sections 4 and 5, and for metal powder grinding in Sections 6 and 7.

2.1 Agent-based technology

Agent-based technology has been successfully applied to the development of industrial, distributed systems (Jennings, Corera and Laresgoiti, 1995; Jennings and Wooldridge, 1998). An agent is a software or hardware program that performs a user-delegated task. It works in a preset environment and interacts with other agents through their logically intelligent programs. The definition of agents used here is the one proposed by Weiss (1999): 'Agents are autonomous, computational entities that can be viewed as perceiving their environment through sensors and acting upon their environment through effectors'. Sensors and effectors can be either physical or software devices.

Agent-based systems can be used to easily create an architecture that delivers the adaptability required for controlling the production of each part in a dynamic process. Each functional agent in this system has a modularized internal structure and is independent from other agents. Such a structure enables the system to be flexible, and thus ensures good adaptiveness (Jia et al., 2004). Part of the adaptiveness is each agent's ability to self-duplicate in order to perform simultaneous, multiple tasks. The ability to add new agents makes the system open and upgradeable.

For the most part, present day control of manufacturing processes is neither adaptive nor dynamic, and it is based on maintaining control variables at or near fixed points, which means that run-up or the start of production after changeover can be a very significant problem (Eldridge et al., 2002). One of the greatest difficulties in designing a good control system is modelling dynamic behaviour as a process varies over time due to non-linearity and variations in materials and operating conditions. For the thermoforming process, material properties vary from batch to batch. Properties such as heater and sheet emissivity, specific heat capacity, sheet density and thermal conductivity vary during the reheat process. Environmental temperatures vary depending on the hour of day and the season. Heating elements age and affect energy output. As a result, for the thermoforming of complex plastic parts, there are typically 3–5 rejected parts during process run-up and a rejection rate of about 5% during production. For new parts, rejection rates are usually much higher.

An adaptive control system, then, needs dynamic capabilities in order to adjust process parameters within a minimum period of time at run-up and to detect drifts during steady state operation. Targeted rejection rates for model-based control of thermoforming are one part during run-up and zero parts during processing. Process models must allow for precise calculations of control parameters and deal with different control parameter response times to accomplish these rates. For example, the effective heating element temperature needs to be continuously calculated during the heating process. The effective heat absorption of each plastic sheet has to be determined due to variations in thickness, molecular weight and emissivity. A simulation establishes optimal heater settings to obtain the desired heating profile. This ability to modify control parameters allows the system to produce near perfect parts by adapting to the continuous changes in the process. In addition, process diagnostics while a process is running permits real time error recovery to maintain quality levels.

3 Agent-based architecture

An agent-based approach was chosen to achieve the required adaptability in a modelbased control system. The main differentiation between an object-based or traditionally programmed control system and an agent-based one is that agents are flexible and autonomous, use encapsulated behaviour, and interact directly with peers to achieve objectives (Wooldridge, 1997). In an agent-based approach, each agent is given its own thread of control and autonomy over its actions. In complex systems such as model-based control, it is impossible to predict all the possible interactions *a priori*; an agent-based architecture is desirable, so that decisions can be made during runtime. Agent interactions are conducted at the knowledge level (in terms of which goals should be followed, at what time, and by whom) compared to method invocation or function calls that operate at a purely syntactic level. Given these facts, an agent-based approach is simply the best fit for model-based control.

The central issues in an agent-based architecture are the responsibilities and the behaviours of individual agents, the coordination of activities among agents, and the communication protocols that are employed. Agents used in this project are reactive agents, which sense their environment either by physical or virtual sensors, and then initiate actions by actuators and/or by communicating with other agents.

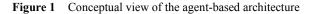
3.1 General architecture

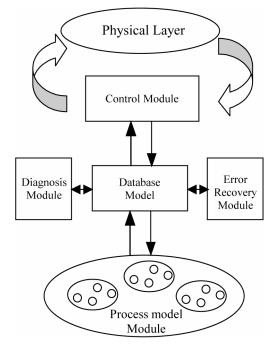
The main features of the architecture are shown in Figure 1. In the agent-based architecture, the system is composed of several modules (agents): control module, process model module or process sub-models, fault diagnosis module, error recovery module, and a real time database in which updated values of process parameters and system state variables are stored. Each agent is continuously active and autonomous, and interacts with other agents whenever required.

The control module must simultaneously handle a number of different tasks. It acquires sensor data, calculates control parameters from the state variables determined by the process model, executes an optimized control plan based on state variables, and delivers the control parameters to the devices in the physical layer.

The process model module can be a single model or a set of many sub-models. Submodels are used when the process cannot be completely represented as one detailed model, and are designed according to the level of sophistication and the time response required for adequate representation of a particular phenomenon for real time control. Each process sub-model is one agent. It performs at its own rate and continuously calculates state variables using sensor data from the database and state variables from other process sub-models. It then updates the state variables in the database that are used by other agents.

The database stores data from the physical layer, all process information as well as state parameters calculated by the process model. The database is implemented as a virtual database resident in computer memory. The database serves as a medium for information exchange in order to improve the efficiency of agent communication. Large amounts of message passing, which are required for real time control, would deteriorate system performance.





The diagnosis module monitors the behaviour of the process. To do this, diagnostics check data from physical layer devices, state variables developed by the process and subprocess models, as well as control parameters calculated by the control module in real time. In addition, checks are made for availability and applicability of physical devices at the beginning of the process. The values of sensor data are continuously evaluated in terms of range and degree of change. Dedicated logistical algorithms assess the interrelationships among state variables within and among process phenomena in order to check the consistency of process models. Detected errors are flagged in the database.

The error recovery module checks for flagged errors, and then, executes preset procedures for error recovery. The error recovery module has access to all the information pertaining to the error, including sensor readings, location, priority of action and so on available in the database. When an error occurs, the affected sub-models are halted. An evaluation of the capability of the production process to continue with reduced data is done. If yes, the exception is handled by agents distinct from the process execution agents in order to correct the problem if possible, and to evaluate when the affected sub-models can resume. For catastrophic errors, an operator is informed about the exception event and intervention is requested.

3.2 Data flow in the system

The control module acquires data from the sensors in the physical layer and sends them to the database. The process and sub-process models then use these measurements to calculate state variables. The values of the resulting state variables are passed back to the database. The control module obtains the values for the state variables from the database,

calculates the control parameters, sends them to be actuated in the process, and then, writes them into the database. During this procedure, the diagnosis module simultaneously evaluates whether the values of the input data, state variables and control parameters are acceptable.

All agents in the control architecture operate independently and asynchronously. The control agent acquires the sensor data and sends the control parameters as they become available. Similarly, the process agents retrieve sensor data and calculate state variables. The retrieval of sensor data and the calculation of state variables are interrupt driven based on the detected variations from previous states; thus, calculations always have access to the best information available. This design permits fast control cycles while allowing data to flow asynchronously. This permits different levels of complexity in the different data streams, while still setting control parameters with validated parameters. The assumption is that during a short production period the few parameters that are not frequently updated do not change very much near the operating point of the process, and thus, do not greatly impact manufacturing until the next update is given. Diagnostics and error recovery operate independently and asynchronously with respect to the process and control modules. Due to the asynchronous functioning of the architecture, it is possible to control processes where sub-model execution times vary from milliseconds to hours.

3.3 Summary

The architecture for model-based control has the following characteristics:

- a process module that continuously evaluates state variables, which can be one large model and/or a set of related sub-models
- a control module that acquires sensor data, calculates control parameters from process model state variables, and transmits the control parameters to the real process
- an independent database model that stores all data as well as calculated process variables, state variables, and control parameters,
- a diagnosis module that validates the sensor data and state variables computed by the process model module
- an error recovery module that either repairs the system while production continues, proposes a 'limp home' configuration, or shuts down the system in case of an irrecoverable error
- asynchronous operation of all control, process model, diagnosis, and error recovery modules
- task execution that is predefined by recipes for action within the discrete set of process states and possible control actions.

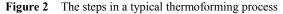
Agent technology is an excellent fit for this architecture because:

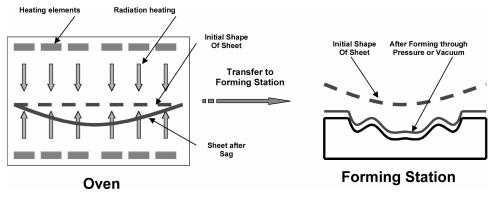
- agents map well to an independent set of tasks
- dedicated agents can manage, calculate or control each data stream

- agents can execute simultaneous tasks (model calculations, simulation and control) and integrate data from multiple sources asynchronously
- agents are suited to the autonomous, distributed processing that is required for highly adaptive control
- agents allow autonomous diagnostics and error recovery, and
- agent technology allows for easy change of architectural components as process know-how grows and process models are updated.

4 Thermoforming process

Thermoforming is a generic term for manufacturing plastic components through a vacuum or a pressure forming process (Throne, 1996). It is composed of three basic phases: heating, forming and solidifying (Figure 2). First, a plastic sheet is heated in an oven between an upper and lower bank of elements to its softening temperature, and then moved to a forming station. There, the sheet is stretched by using vacuum or air pressure, often with the aid of a plug to form the plastic in order to achieve complex details. Finally, when the plug is removed, cool air is blown into the mould for faster solidification. The part is then removed and excess plastic is trimmed away.

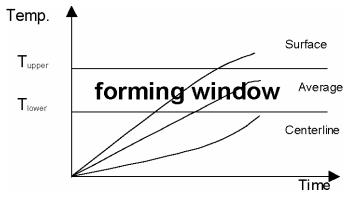




Thermoforming is a high waste process, which means that the process has a lot of room for improvement in production efficiency, energy and material use as well as part quality. Research on the thermoforming process shows that the most critical phase is sheet heating, which directly affects subsequent phases of the process. Close temperature control during this phase results in reduced part rejection, decreased energy consumption, and shortened cycle time.

As shown in Figure 3, thermoforming materials have forming windows defined by a lower (T_{lower}) and upper (T_{upper}) forming temperature. A polymer material surface is prone to colour change or blistering if the surface temperature goes above T_{upper} . On the other hand, the polymer is too stiff to be formed or will have micro-cracks while being formed if the plastic is below T_{lower} at forming. The lower and upper temperatures determine the processing window, which can be quite small for some new 'designer' polymers.

Figure 3 Plastic sheet heating for thermoforming showing the temperature limits of the forming window as well as the surface, centre, and average temperatures



In thermoforming, the heating process is controlled by the rate at which energy is delivered to the plastic sheet internally by radiation and to the surface by convection. The energy transferred to the sheet controls the heating time. The primary purpose for the control of the thermoforming process is to transfer the correct amount of energy required to heat the plastic sheet and to maintain the temperature within the forming window (between T_{lower} and T_{upper}), while realizing the desired temperature distribution across the sheet. For a thin sheet, the internal temperature of the sheet is practically the same as the surface temperature. For a thick plastic sheet, the heating time can be calculated from the heat capacity and volume of the sheet and the combination of the plastic sheet during heating needs to be controlled to correctly thermoform a thick sheet, since it cannot be measured directly.

In a thick sheet, the temperature at the centre of the sheet is significantly below the surface temperature due to the relatively slow thermal diffusive character of polymer sheet. Note that in Figure 3, the thermoforming process is not correctly controlled, i.e., the surface temperature is above the upper temperature, while the temperature at the centre of the sheet is not yet at the lower temperature limit to allow forming. If this scheme were to be used for energy input, this sheet temperature profile would result in a rejected product. To ensure proper sheet heating, the controller must adjust the energy transfer rate, i.e., the element temperature and/or the length of stay in the oven. Better control of individual heating elements to achieve the desired sheet temperature distribution results in better formed parts since good temperature distribution yields the required material thickness distribution for the finished part. Improved control of material distribution increases part quality. This results in fewer rejects and allows for parts with a higher technical content to be produced on an existing machine. Using less energy and material for forming the same part also increases production efficiency. With adaptive control, it is possible to set the control tactic to heat the sheet of plastic to a fixed time (coordinate sheet heating with other fixed automation) or to the minimum time (maximize part production). For each scenario, the amount of energy used is minimized.

5 Control of the thermoforming process

The first step for the creation of a model-based control system using agents is to build a process model and simulator. The process model determines critical state variables and the simulator simulates the process to predict desired outcomes given the state variable history. For every part made, FormView¹ is used to provide a finite element simulation of the thermoforming process to predict the time sequenced trajectories of the heating elements and the sheet temperatures for different sheet zones. However, since the thermoforming process is non-linear and multi-parameter, the computing time for FormView makes it unsuitable for real time control. Therefore, three other sub-models with a suitable precision and time response were created to approximate process behaviour for critical process variables. Since the FormView simulation is relatively accurate, FormView uses the sub-models to adjust variables in the vicinity of the predicted operating point until the next update.

The first process sub-model is a model to predict heating element surface temperatures based on the power input. The second sub-model calculates the internal temperature distribution of the plastic sheet based on mathematical models of the process and measured sheet surface temperatures. This sub-model uses a virtual sensor technique, i.e., the use of an algorithm to estimate inaccessible state variables using measurable parameters. The third sub-model is a sheet heating model. The inputs to the sub-model are heater surface temperatures and internal sheet temperature distributions that are generated by the previous sub-models. The output of the sheet-heating sub-model is a map of sheet surface temperatures.

The simulator and the sub-models are each executed by an agent. The other agents in the control system execute the control module as well as the diagnosis and error recovery modules that were described earlier.

5.1 Implementation

For implementing the agent-based architecture for thermoforming, the Java Agent DEvelopment framework (JADE) software was used. JADE is a framework fully implemented in Java language. Since Java supports major network protocols, it is feasible to use JADE for the development of agent-based systems within a network environment. JADE simplifies the implementation of multi-agent systems through middleware architecture, i.e., higher-level libraries that enable easier and more effective application development. Middleware provides better, OS independent, Application Program Interfaces (APIs) to simple and reusable building blocks (Bellifemine et al., 2003).

The complexity of the middleware is hidden behind an intuitive set of APIs. The following is the list of JADE features:

- a distributed environment composed of several agent containers launched over one or more host computers across a network
- a graphical user interface to manage several agents and agent containers from a remote host
- intra-platform agent mobility, including transfer of both the state and the code (when necessary)

- support for the execution of multiple, concurrent agent activities via a behaviour model
- a FIPA (Foundation of Intelligent Physical Agents) standard platform.

When JADE is used as the platform to implement a real time agent based system, specific requirements for the properties of the platform such as speed, memory, reliability, etc., must be met. Studies have been performed to evaluate JADE performance (Cortese et al., 2003). Regarding memory requirements, measurement has shown that the JADE platform requires a minimum of 100 Kb of runtime memory, which is small enough to fit well within the capacity of the majority of automation controllers. The speed of message delivery is another important feature of JADE. In order for the agent platform to be fast enough for real time control, it should be able to carry out interactions among agents and message delivery on the order of milliseconds or tens of milliseconds. Cortese et al. (2003) have evaluated the performance of the JADE messaging subsystem. Results showed that JADE is a good candidate for heavily loaded, distributed applications since it scales linearly with load conditions. JADE is currently available as an open source code.

6 Powder ball milling

The current market for powder metallurgy products is 70% automotive, 15% appliances, 12% business machines and 3% farm and garden equipment (DeGarmo, Black and Kohser, 1988). The powder metallurgy process generally consists of four basic steps: metal powder production, mixing, compacting and sintering. Chemistry, purity, particle size distribution, particle shape and surface texture are important properties and characteristics of metal powders.

A model-based control system for metal powder grinding was developed with a company that produces metal powder products, where the key control output was production of the desired particle size distribution. The grinding process is performed in dry conditions and in an open circuit, i.e., no recirculation of coarse product. A melt of high carbon iron is atomized by water jets into granular 'shot'. The shot is fed into a ball mill where, as the cylinder rotates, lifters inside the structure create a tumbling effect of steel balls, which fracture the shot into powder. Because of its high carbon content, the shot is very brittle and can be easily ground to the required size. Once the particles reach the desired size, they are swept away by the airflow generated by a downstream blower equipped with a damper. Then, the powder is mixed with ground mill scale (iron oxide). The carbon from the powder and the oxygen from the mill scale combine in a belt furnace at sintering temperatures. Carbon monoxide (CO) gas forms, leaving a pure iron cake. Finally, the cake is disintegrated and refined to powder size.

The ball milling operation is critical to this process since it determines many characteristics of the final metal powder product: density, dimensional change, green strength, compressibility and so on. Based on the desired size distribution and density, the operator adjusts the following ball mill parameters: feed rate, airflow and level of balls in the mill. It is very hard to establish a standard operational procedure since multiple parameter combinations are possible to achieve the desired results.

There have been several models and control systems already developed for closed circuit (coarse particle recirculation) wet ball milling for the mining industry (Pomerleau et al., 2000; Apelt, Asprey and Thornhill, 2001; Conradie and Aldrich, 2001). Modelling

and control of closed circuit cement mills is described by Topalov and Kaynak (2004). Still, these models do not adequately account for the non-linear nature of the ball milling process, and do not perform well enough to achieve the required quality level for metal powder ball milling.

The lack of adequate process models means that present day ball milling operations still generate large variations in powder properties, which result in poor end product performance. A new ball milling process model was therefore created to reduce product size variations and maximize throughput by integrating process sub-models composed of rules, equations and heuristics. Kookos and Perkins (2002) point out that heuristic and logical rules can create a feasible control structure.

Ball mill product quality is defined by a precise and stable size distribution as well as its apparent density. It was expected that the performance of a model-based controller would be greatly influenced by the frequency at which product properties were input into the control module. Plant trials confirmed this and also showed that apparent density is directly proportional to size distribution. Hence, size results alone are sufficient to characterize and control ball mill product properties. An automatic sampler was therefore created to work in conjunction with a fully automated sieve analyzer, providing frequent feedback of output powder size distribution to the control system.

7 Control of powder ball milling

The agent-based architecture defined in Section 3 allows adaptive control of ball milling using agents to respond to variations in product recipes and process behaviour. Deep process knowledge of ball milling permitted the establishment of a new control strategy; namely,

- maximize breakage rates with feed rate variations based on inferential measurement of powder charge using power use data, and
- control output properties by adjusting airflow based on size results.

A ball mill model was developed for all the process variables and the various procedural and decision rules. The model was created based on mathematical models of ball milling, the knowledge of the most experienced ball mill operators, and plant trial results. The process model was composed of seven related sub-models, each of which is executed by one agent, operating at a different cycle time. The first sub-model predicts the inside grinding volume of the mill as a function of liner wear to control grinding ball height using a 3-D model of the interior shell. The second sub-model calculates the continuous ball feed rate to compensate for ball and liner wear based on a mathematical model using measured ball bed height, ball usage and run time. In the third sub-model, inference measurement of powder charge is accomplished with a mathematical model and direct measurement of power use. The maximum breakage rates are obtained approximately at maximum power use, depending on liner condition and ball load. The fourth sub-model computes the mean residence time using measured shot feed rate and estimated powder charge. The number of impacts influences the disintegration and attrition of particles and the product shape. The fifth sub-model evaluates the production rate based on measured shot feed rate, dust rate and virtual sensor variation of powder charge with respect to time. The sixth sub-model regulates shot feed rate, which is a very important output

control variable that dictates productivity, residence time, powder charge, and product properties. The seventh sub-model evaluates product size feedback with a set of rules to generate new airflow set points. Airflow rate prescribes product size distribution and product properties. An example of sub-model six for the input feed rate is shown in Figure 4. The rules in Figure 4 define the feed rate set point, \dot{m}_{sp} (kg/hr), based on the

mill power use, P (kW), given the optimum power use, P_{opt} (approximately at the maximum breakage rate).

Figure 4 Rule-based feed rate sub-model provides a set point for the controller, which sends the shot feed rate control variable to the process

$\overset{\text{th}_{\text{set point}}(S)}{\longleftarrow} \underbrace{E(s)}_{C(s)} \underbrace{U(s)}_{C(s)} \underbrace{U(s)}_{C(s)}$	+ 	Feeder $G(s)$ $in(s)$
$if \ P \ge P_{opt} + 17$	then	$\dot{m}_{sp}=\dot{m}_{sp}-400$
$if P_{opt} + 12 \le P < P_{opt} + 17$	then	$\dot{m}_{sp}=\dot{m}_{sp}-300$
<i>if</i> $P_{opt} + 7 \le P < P_{opt} + 12$	then	$\dot{m}_{sp}=\dot{m}_{sp}-200$
$if P_{opt} + 2 \le P < P_{opt} + 7$	then	$\dot{m}_{sp} = \dot{m}_{sp} - 100$
<i>if</i> $P_{opt} - 2 < P < P_{opt} + 2$	then	$\dot{m}_{sp} = \dot{m}_{sp}$
$if P_{opt} - 7 < P \le P_{opt} - 2$	then	$\dot{m}_{sp} = \dot{m}_{sp} + 100$
$if P_{opt} - 12 < P \le P_{opt} - 7$	then	$\dot{m}_{sp} = \dot{m}_{sp} + 200$
<i>if</i> $P_{opt} - 17 < P \le P_{opt} - 12$	then	$\dot{m}_{sp} = \dot{m}_{sp} + 300$
if $P \le P_{opt} - 17$	then	$\dot{m}_{sp} = \dot{m}_{sp} + 400$

The control module to compute the output control parameters uses variables from the process sub-models: shot feed rate, airflow and ball feed rate. They are then sent to the physical process.

Diagnostics of air pressure permit adaptive control of the airflow. This approach simplified the implementation of airflow rate set points for the control model. The diagnostic system also monitors product apparent density and advises plant personnel of out of specification product.

7.1 Implementation

The controller architecture for powder ball milling was implemented using a PLC manufactured by Omron. It is composed of a central processing unit, communication board, backplane, I/O digital units, I/O analogue units, temperature sensor units, DeviceNet master unit, remote I/O digital units, remote I/O analogue units, and remote temperature units. A human machine interface manufactured by Exor is linked to the PLC to allow the operator to visualize and control the ball milling process.

PLC's are desirable in an industrial environment due to their low cost, robustness and flexibility. Agents were programmed as contact-ladder diagrams using the CX-Programmer software, designed for use with Omron PLC's. Messages from all process sub-models, the control module and sensors were exchanged by means of the PLC

database. This provided data sharing and a mechanism to exchange ladder variables for the dynamic execution of agents.

8 Results

Model-based control for thermoforming has given excellent results; there are less rejects at start up, better part quality, reduction in energy use and more control over cycle time. To date, experiments have been limited to a small number of parts due to very high material costs. However, the new system is being installed at an auto part manufacturer, where more performance statistics will be available with larger part production. There is every expectation that the target of one poor part during run-up and zero rejected parts during processing will be achieved.

System performance of the agent-based controller for powder ball milling was tested during the production of metal powder. Product size results were obtained by manual sampling and testing every 15 minutes; test results were then fed into the controller. Manual sampling and subsequent control was done since an automatic sampler was being built. Due to the slow response time of the ball mill process, this did not pose a problem. Results for the production of metal powder without and with model-based control are shown in Table 1.

Table 1Apparent density, ρ_o , and percentage powder passing a 200 mesh (75 µm), S200, for
metal powder without and with model-based control

Process parameter	$ ho_o \left(g/cm^3 ight)$	S200 (%)
Without controller ($\mu \pm 3\sigma$)	3.30 ± 0.41	62.5 ± 15.7
With model-based control $(\mu \pm 3\sigma)$	3.19 ± 0.08	63.1 ± 2.1

Output powder size distribution is often defined by a single point measurement, such as the percentage passing a 200 mesh (75 μ m) sieve. Once the model-based controller was activated, the required product property specifications were achieved within 30 minutes and maintained within the above accuracy and precision. The variation in the powder size distribution was reduced from 15.7 to 2.1% at a 99.73% confidence interval, an excellent result that met all expectations.

9 Discussion

The goal of model-based control for any process is to have in-cycle control, i.e., to be able to adjust processing parameters during the production of a part or product. To do this, the computing time from the analysis of sensor data through the calculation of state variables to obtaining control parameters must be much shorter than the cycle time. However, certain data can only be measured after a part is made, for example, part thickness in thermoforming. In this case, if accurate predictors for such state variables cannot be designed, control can only be done cycle-to-cycle, and most likely, with a time gap of many parts. This information must be integrated with other data in order to have a coherent picture of the process. Depending on how critical the sensor data is for the calculation of state variables, some processes may only be able to be controlled cycleto-cycle. The design of the agent-based architecture allows control to be adjusted while

the product is being made even though all process parameters cannot be measured in the same time frame.

The control architecture is designed using asynchronous agent execution that guarantees a fast response time for process control. To assist asynchronous execution, there is no direct message passing among agents; communication is facilitated through the use of the database module. This technique avoids the high overhead of direct message passing, simplifies the design of the control system, and further reduces execution time. Not having direct message passing does not affect the functions performed by agents or their ability to co-ordinate activities.

Control of manufacturing processes is by nature real time. There are constraints imposed by the process since the product has to be made within the optimum period of time and the material processing boundaries. For example, for in-cycle control of thermoforming, decisions typically have to be made and implemented in the first 5–10% of the fabrication cycle to be able to correct a potential defect in the part currently being produced. If decisions cannot be made this rapidly, then, control can only be done cycle-to-cycle with a resulting increase in reject rates. In-cycle control is always preferable since it allows adjustment of the process for each part, and thus, ensures better part quality and lower rejection rates.

The architecture described in this paper can handle hard real time. This can be done with a single processor, if the amount of computation is small. Nevertheless, for a process like thermoforming, the amount of calculation for process models tends to be large and distributed over different time frames; therefore, multiple processors may be required depending on the complexity of the heating process. With multiple processors, the control system can dynamically allocate the execution of different agents to available processors. This allows great flexibility to respond to variable amounts of computation and to respond to fast cycle times.

The architecture for model-based control allows more control transparency and less operator intervention. This greatly improves interoperability. Model-based control makes interaction with control systems simpler and more uniform for machines of different ages from different vendors with different control systems, and interfaces to machines can be made conceptually similar and operationally almost identical. This is possible because process and control information is in the control system and not with the operator. Such systems can also be centrally managed. Interoperability between companies is also improved since model-based control reduces the variability of production and since standard production data is available for each part or product.

10 Conclusions

The application of intelligent agents to process control has proven to be very effective. Controllers for thermoforming based on the agent-based architecture described in this paper are now being implemented. Agent-based control is self-tuning; so, rejection rates at run-up and during production can be kept to a minimum. In addition, the system provides for easy adjustment of parameters as the environment changes or when changeover occurs. The target of one rejected part during run-up and zero rejects during processing means moving from a quality regime of two sigma to six sigma. This is only attainable with the responsiveness of model-based control. Agent-based control systems for thermoforming and metal powder ball milling have achieved excellent results. The flexibility of the agent-based architecture is illustrated by the fact that it was implemented for two different applications, one on a standard processor using JADE and the other on a programmable logic controller.

The agent-based architecture is effective and has the adaptability needed for the control of complex processes. Control based on process modelling also permits easily interpretable diagnostics and error recovery. Parallel processing allows real time response regardless of the process complexity and cycle time. Finally, agent-based control is applicable to any process where state parameters can be induced from process know-how.

References

- Apelt, T.A., Asprey, S.P. and Thornhill, N.F. (2001) 'Inferential measurement of SAG mill parameters', *Minerals Engineering*, Vol. 14, pp.575–591.
- Bellifemine, F., Caire, G., Poggi, A. and Rimassa, G. (2003) 'JADE a white paper', *TILAB EXP* in Search of Innovation, Vol. 3, pp.6–19.
- Conradie, A.V.E. and Aldrich, C. (2001) 'Neurocontrol of a ball mill grinding circuit using evolutionary reinforcement learning', *Minerals Engineering*, Vol. 14, pp.1277–1294.
- Cortese, E., Quarta, F., Vitaglione, G. and Vrba, P. (2003) 'Scalability and performance of the JADE message transport system', *TILAB - EXP in Search of Innovation*, Vol. 3, pp.52–65.
- DeGarmo, E.P., Black, J.T. and Kohser, R.A. (1988) *Materials and Processes in Manufacturing* (pp.376–392). New York: Macmillan Publishing.
- Eldridge, C., Mileham, A., McIntosh, R. Culley, S., Owen, G. and Newnes, L. (2002) 'Rapid changeovers – the run-up problem', Paper presented at the 18th ISPE/IFAC International Conference on CAD/CAM, Robotics & Factories of the Future (pp.161–168). In proceedings.
- Jennings, N.R., Corera, J.M. and Laresgoiti, I. (1995) 'Developing industrial multi-agent systems', Paper presented at the *ICMAS*'95 (pp.423–430). In proceedings.
- Jennings, N.R. and Wooldridge, M.J. (1998) 'Applications of Intelligent Agents', In N.R. Jennings and M.J. Wooldridge (Eds), Agent Technology: Foundations, Applications, and Market (pp.3–28). New York: Springer.
- Jia, H.Z., Ong, S.K., Fuh, J.Y.H., Zhang, Y.F. and Nee, A.Y.C. (2004) 'An adaptive and upgradeable agent-based system for co-ordinated product development and manufacture', *Robotics and Computer-Integrated Manufacturing*, Vol. 20, pp.70–90.
- Kookos, I.K. and Perkins, J.D. (2002) 'An algorithmic method for the selection of multivariable process control structures', *Journal of Process Control*, Vol. 12, pp.85–99.
- Pomerleau, A., Hodouin, D., Desbiens, A. and Gagnon, E. (2000) 'A survey of grinding circuit control methods: from decentralized PID controllers to multivariable predictive controllers', *Powder Technology*, Vol. 108, pp.103–115.
- Throne, J.L. (1996) Technology of Thermoforming. Cincinnati, USA: Hanser Publishers.
- Topalov, A.V. and Kaynak, O. (2004) 'Neural network modeling and control of cement mills using a variable structure theory based on-line learning mechanism', *Journal of Process Control*, Vol. 14, pp.581–589.
- Weiss, G. (1999) Multiagent Systems. Cambridge, USA: The MIT Press.
- Wooldridge, M. (1997) 'Agent-based software engineering', Paper presented at the *Ins.Elec.Eng.*, Vol. 144, pp.26–37. In proceedings.

Note

¹A plastic forming software distributed by the Industrial Materials Institute (IMI), National Research Council (Canada), Montreal.