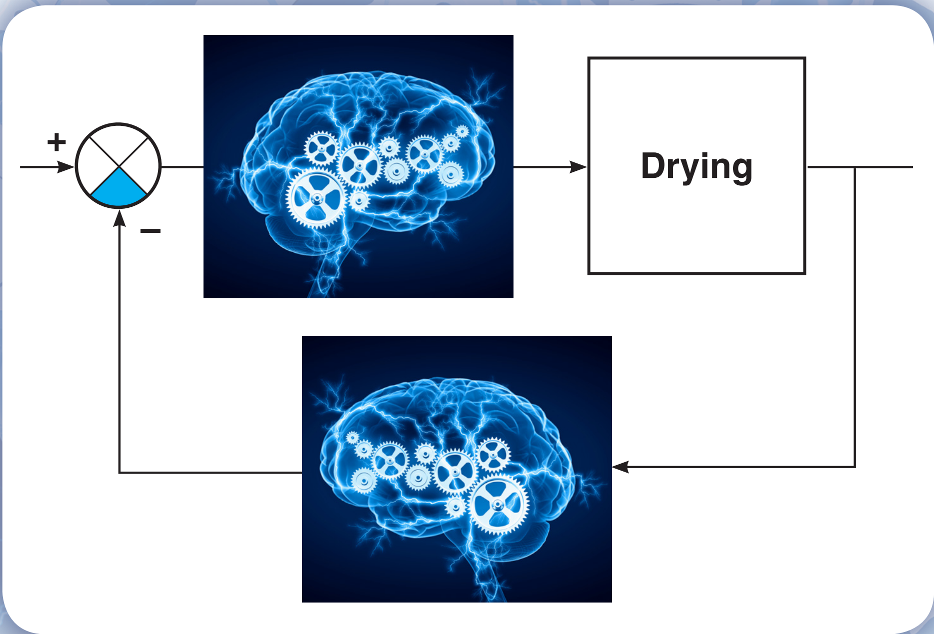
ADVANCES IN DRYING SCIENCE AND TECHNOLOGY

INTELLIGENT CONTROL IN DRYING



edited by
Alex Martynenko
Andreas Bück

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Intelligent Control
in Drying

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Intelligent Control in Drying

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To the loving memory of my father, Ivan Martynenko,
one of the founders of the Scientific School in
Control and Automation in the Ukraine

Alex Martynenko
Truro, Canada

To my family

Andreas Bück
Erlangen, Germany

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Acknowledgments

This book was inspired by Professor Arun S. Mujumdar, who is constantly looking for innovations in drying. Thank you, Arun, for the great opportunity to prepare this book, which is unique in the sense that it is the first attempt to put together the expertise of the international drying community working on *smart* drying technologies with the elements of artificial intelligence.

The editors thank all of the contributors and reviewers for their efforts in preparing, reviewing, and revising the contributions collected in this book. Special thanks to Dr. Tadeusz Kudra for his invaluable professional contribution in reviewing and proofreading the entire book. Furthermore, the continuing support of Allison Shatkin at CRC Press, Taylor & Francis, in the organization, finalizing, and processing of the book is gratefully acknowledged.

Introduction

Drying is one of the oldest conservation techniques known to man. Although it has been applied for millennia, it still poses a challenge today with respect to preservation of key components of the dried material, even more so, if the material is to be dried on a large scale and is subject to seasonal or local changes in its composition. As such, the study of drying processes is the simultaneous study of heat and mass transfer of in many cases porous materials at the interface with materials science. In order to achieve required throughputs, maintain product quality, and fulfill economic constraints, control of drying processes is increasingly in demand.

Intelligent control is a multidisciplinary area at the interface of control theory, expert systems, automation, computer vision, sensor fusion, operations research, and artificial intelligence (AI). Despite abundant literature in the area of intelligent control, there is a definite lack of knowledge and general know-how in practical applications of intelligent control in drying. The intent of this book is to fill this gap.

Intelligent Control in Drying is anticipated to be an innovative and practical handbook for researchers and professionals in the area of drying technologies. It provides an overview of state-of-the-art control principles and systems used in drying operations, from classical to model-based to adaptive and optimal control. At the same time it lays out approaches to synthesis of control systems, based on the objectives of drying and control strategies, reflecting the complexity of the drying process and materials under drying.

Product quality and energy efficiency are usually two major objectives of drying. Although some drying processes could be well-described by models with acceptable accuracy, there is always some uncertainty in combined effects of drying factors on the mass transfer. This challenge, especially important in the development of hybrid/advanced drying technologies, requires optimization of drying. However, optimization is usually specific for a particular drying technology and material under drying. Another step forward is based on intelligent control strategies, which are equally applicable to any drying scenario. Current research and development in intelligent control has been driven by recent advances in drying technologies and computer-aided instrumentation.

The scope of this book covers both fundamental and practical aspects of intelligent control, sensor fusion, and dynamic optimization with respect to drying. It consists of two parts.

Section I: *Basics of Intelligent Control* envelops most of the topics related to intelligent control, including a brief history of intelligent machines, instrumentation and software for computer-aided control, adaptive and model-based control, estimation of model parameters, static and dynamic optimization, control by neuro-fuzzy and evolutionary algorithms, and basics of machine learning. Special attention is paid to the development of control strategies and dynamic optimization in drying. The benefits of intelligent control for optimization of drying processes are thoroughly discussed.

Chapter 1 introduces to readers to the history and art of intelligent machines from the Jacquard loom to spacecraft navigation. Briefly discussed are what makes machines intelligent, the evolution in machine intelligence, learning, and reasoning as required ingredients of intelligent machines, as well as societal and ethical implications of AI.

Chapter 2 describes challenges and benefits of computer-aided control and explains how computer applications could improve drying processes. The chapter focuses on practical aspects of observability and controllability of drying, in particular *smart* sensors and instrumentation for real-time measurements, which are prerequisites for intelligent control. Control of the product under drying is differentiated from control of the drying environment. Computer interfacing with the analog world, as well as software for data acquisition, process monitoring, control, and optimization are discussed and a motivational example of computer-aided control for ginseng drying is given.

Chapter 3 provides an introduction to estimation of the structure and parameters of mathematical models from a limited number of experiments. Different modeling concepts and notions of model identifiability are discussed. It is proposed that model parameters are determined by the solution of inverse problems, while uncertainty is estimated through the diagonal elements of a covariance matrix. This approach could also be used for online estimation of model parameters in the process of drying. The proposed approach is illustrated with computational examples of food drying in fluidized bed.

Chapter 4 introduces the reader to general concepts and terminology of model-based control, including open-loop, closed-loop (feedback), optimal, and adaptive control. Practical aspects of robust control, as well as observability, controllability, stability, and dynamics are briefly discussed.

Chapter 5 covers in an informal manner the main concepts of static optimization, that is, steady-state or equilibrium models and some methods commonly applied in the area of drying technology. The mathematical background to optimization, such as the cost function and constrains, is introduced. Three classes of optimization models, first principle models, neuro-fuzzy models, and response surface models (RSM), along with relevant experimental design for each class, are briefly discussed. Methods of constrained and unconstrained optimization and their applications in drying technology are presented.

Chapter 6 gives a basic introduction to the mathematical background of dynamic optimization, numerical methods to solve the optimization problem, and model requirements. Calculation of optimal trajectories is based on evaluation of the Hamiltonian of the objective function. Alternative simple algorithms for dynamic optimization, based on piecewise linear approximation and optimization of spatially distributed processes are presented. For better understanding the concept of dynamic optimization this chapter is illustrated with examples of batch drying of tea and broccoli.

Chapter 7 presents a condensed overview of adaptive feedback control design, starting with a motivation and a description of the main principles. An overview of different adaptive concepts is given that include gain scheduling, model reference adaptive control (MRAC), self-tuning regulator (STR), dual control, and auto-tuning. The advantages of adaptive control are demonstrated with two examples of MRAC and auto-tuning control applications for spray drying and conveyor-belt drying.

Chapters 8 through 10 introduce soft computing techniques, such as artificial neural networks (ANNs), fuzzy logic, and evolutionary algorithms. Chapter 8 provides an overview of fuzzy logic fundamentals and applications for advanced modeling and control of drying processes. Chapter 9 focuses mainly on ANN applications, providing an overview of the most important research works conducted on the application of this technique in drying technology. The ANN technique has been widely used for function approximation, pattern recognition, optimization, control, and classification problems. Chapter 10 focuses on genetic algorithms (GAs) and their typical applications for identification and control in drying processes. Identification of model parameters is illustrated with the example of exponential model of drying kinetics, control is illustrated with example of fluidized bed dryer, and optimization with respect to both the quality and energy is illustrated with the examples of the conveyor-belt and infrared dryer. Different aspects of GA applications for intelligent control are briefly discussed.

Chapter 11 introduces inexperienced readers to techniques of machine learning as a prerequisite for intelligent control. Numerous techniques of supervised learning, such as support vector machines (SVM), random forest classifier (RFC), multilayer perceptron (ANN), convolutional neural networks, and recurrent neural networks (RNN), are explained. The concepts of deep probabilistic machine learning, reinforced machine learning, and Bayesian modeling are introduced. Considering that machine learning is a not commonly used technique in drying, potential areas of application to food drying are discussed.

Section II: Applications of Intelligent Control in Drying presents examples of practical implementation of intelligent control. Case studies with air convective, microwave, freeze, and fluidized-bed drying present examples of industrial drying applications with the elements of intelligent control. This broad range of topics, approaches, strategies, and application examples will be useful for engineers and scientists, as well as graduate students who want to learn more about this exciting subject.

Chapter 12 proposes an intelligent drying control strategy based on monitoring and control of product temperature instead of air temperature. This strategy is particularly suitable for heat-sensitive products, such as fruits and vegetables. The implication of this control strategy is non-isothermal (variable temperature) drying, resulting in better quality of the product.

Chapter 13 elaborates on the concept of non-isothermal drying, proposing product cumulative thermal load as an indicator of drying process intensity. Monitoring and control of product temperature allows for distinction of two phases of drying, when product temperature becomes equal to wet-bulb temperature. Two control strategies are explored: (1) high air temperature in the first phase, followed by a lower temperature in the second phase; and (2) low temperature in the first phase followed by increase of temperature in the second phase.

Chapter 14 provides an example of intelligent control of apple and kiwifruit drying, based on a computer vision system (CVS). Monitoring of quality attributes and energy consumption allowed for improvement of hybrid (hot air-infrared) drying by choosing optimal control strategies. The concept and engineering design of intelligent integrated control using CVS and a fuzzy logic controller for a thin-layer fruit drying is discussed.

Chapter 15 presents examples of applications of neural networks and software sensors in drying technology with the focus on control strategies. To illustrate how these techniques can provide useful information for process control, three cases are discussed. In the first case study, an ANN is used to predict the coupling term in a model designed to estimate the temperature and moisture dynamic behavior in spouted-bed drying pastes. In the second case study, the ANN model allows for the application of a single network to estimate the drying kinetics of heterogeneous composition of aromatic herbs for a wide range of operating conditions. In the third case study, an ANN is designed to estimate the residence time distributions of solid wastes in a rotary drum dryer. Based on the case studies, it is demonstrated that the combination of ANN with software sensors is a powerful tool to overcome the numerous drawbacks of purely mechanistic models of drying kinetics.

Chapter 16 presents an overview of challenges in microwave drying, such as nonlinear interaction of the material with the external electromagnetic field, nonuniform distribution of temperature and moisture content, all causing motivation for feedback control. Case studies of feedback controller design for different microwave drying applications, such as spatially averaged temperature and moisture content, spatial distribution of temperature, and spatial distribution of temperature and moisture content in a porous solid material are presented.

Chapter 17 focuses on theoretical solutions for automatic control of microwave dryers using software programming codes to couple mathematical models with dryer control. Both lumped and distributed mathematical models of microwave process are presented. A mathematical model, coupling heat and mass transfer in MW drying, was developed to control drying of granular agricultural products, such as cereals and oilseeds.

Chapter 18 introduces the reader to challenges and limitations in spray drying. Classification of process models and control strategies, appropriate to achieve specific control objectives, are provided. The applications of open-loop control, static optimization, feedback control, and optimal control for spray drying are thoroughly discussed with references to the pertinent research.

Chapter 19 presents an overview of two control strategies in freeze drying, namely control of the pressure in the heating chamber and/or control of the heating power. The first strategy is based on the pressure rise test, a technique for the in-line process identification that allows estimating both the state of the product (temperature and residual amount of ice) and the model parameters. The second strategy exploits product temperature to optimize only the temperature of the heating element. Experimental measurements are coupled to a fuzzy logic model, representing software sensors. In-line optimization aims at minimizing duration of the freeze-drying and maximizing the end product quality. Examples of applications of both approaches for process design, lab-scale units, and process management in industrial-scale dryers are given.

Chapter 20 provides an overview of control problems in fluidized bed drying. Feedback control of fluidized bed drying is a challenging task because of the interaction between the process inputs and the outputs. Controller design study is illustrated with examples of SISO, MIMO with static decoupling, and MIMO PI feedback control. If state feedback is used, comfortable means exist to find control laws that are optimal in a certain case, for instance, with respect to the closed-loop dynamics or minimal control effort.

Chapter 21 presents an introduction to control of conveyor-belt dryers, representing a spatially distributed system with significant disturbances (variations of inlet moisture content) and time delays (influenced by the belt velocity) at the outlet. Such problems of distributed control can be alleviated in at least two ways: installation of additional measurement probes along the length or width of the dryer or the use of process control algorithms suitable for managing time delays, for example, the Smith predictor. An optimal performance can be achieved using instrumentation for early detection of process disturbances and model-based predictive control, for example, quadratic dynamic matrix control (QDMC).

The application part is followed by a thorough discussion of future trends in AI developments for the benefit of drying technologies. It is expected that future AI applications in drying will focus mostly on three areas: (1) development of software sensors and their combinations with soft computing algorithms (ANN, fuzzy logic, evolutionary algorithms), (2) machine learning and knowledge accumulation about new drying processes and phenomena, and (3) multi-objective optimization of product quality and energy efficiency.

Editors

Alex Martynenko is professor of bioelectronics and bioinstrumentation at Dalhousie University in Nova Scotia, Canada. He earned his Bachelor of Science in agricultural engineering from the National Agricultural University of Ukraine and his Masters of Science in agricultural engineering from Moscow Agroengineering University. Working on the edge of biological science and engineering, he is developing innovative drying and food-processing technologies. While at the University of Guelph in Ontario, Canada, where he received his PhD, he developed minimal processing technology for ginseng root drying. This technology, developed for Ontario ginseng growers, significantly decreases energy requirements and improves the quality of ginseng drying. In 2007, he established a framework for a strong and innovative imaging research program at Dalhousie University, with an emphasis on two major research themes: (1) multispectral imaging of food quality in drying and (2) optimization in drying operations. Throughout his career, Dr. Martynenko has successfully managed a number of research projects related to the engineering of innovative processing technologies and control systems. He has successfully completed 28 research projects, including three international projects, and presented the results of his research in peer-reviewed scientific journals (62) and at international conferences (46). He is an author and coauthor of four books and 10 patents, requested author of two reviews in drying technology, and an instructor for industry-oriented short courses.

Andreas Bück holds a Doktoringenieur (PhD) in chemical engineering and a Diplomingenieur in engineering cybernetics (control engineering), both from Otto von Guericke University, Magdeburg, Germany. After several years as assistant professor for particle formation processes in fluidized bed processes, he is now professor for “Particle Technology” at Friedrich-Alexander University, Erlangen-Nuremberg, Erlangen, Germany, heading a research group on solids processing. His main research focuses on the investigation of particle formation processes—drying, granulation, agglomeration, crystallization—as well as development of online/inline measurement techniques, and process control schemes for these processes. He has (co-)authored more than 50 peer-reviewed works in scientific journals in these areas since 2013 and has contributed to several standard references in the fields of drying, heat transfer, and particle formulation.

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Section I

Basics of Intelligent Control

1 The History of Intelligent Machines

John Elliott and Alex Martynenko

CONTENTS

Until the Jacquard loom of about 1799, many automatic devices were designed to perform only one function. Prehistoric fountains would close a valve when an assigned water level was reached. Hero's steam apparatus would open or close a door depending on circumstances. Early sound recording devices similarly created a stylus mark on a clay or wax cylinder which could later be used as a playback pattern. Medieval animatrons (artificial animals or people) would perform a set of physical activities in a prescribed sequence. In the latter case, gears, weights, springs, and pulleys were the usual motive and organizing agents.

Jacquard's innovation was to develop a way that a machine could perform different functions. Different weaving patterns could be commanded by placing different patterns of holes on a cardboard that controlled the loom arms. Patterns could be sequenced by feeding one card after another to the loom (Figure 1.1).

By the 1840s, Ada Lovelace proposed the same approach for Charles Babbage's Analytical Engine. His first device, the Difference Engine, had a single purpose—to compose tables of numbers. The Analytical Engine was to be multi-purpose, based on Ada Lovelace's if-then rules. The commands would be given by arrangements of slots on cards that would be fed to the machine. Although a detailed layout of the Analytical Engine was developed, the prototype of the device has never been built.

Devices commanded by slots on cards were also developed in the late 1800s as player pianos. When a pianist struck a piano key, a specific slot would be cut on a card. The piano could then replay the piece by connecting the slots to the piano keys. At the very end of the typewriter era, as word processors entered the office, some typewriters maintained a kind of mechanical memory by having each key strike a soft clay that held the key shape. The typewriter could retype to paper whatever had been marked in the clay or wax.

The Jacquard loom and Lovelace/Babbage command by slots on paper or cardboard represented the step towards machine or hardware, which could have multiple purposes

FIGURE 1.1 Jacquard loom with punch cards ca. 1840. (From Smithsonian NMAH.)

because of software. Lovelace, for example, suggested that the Analytical Engine might move beyond numbers to deal with music and other arts. Interestingly, that single-purpose machine programmed by its initial design did not require human presence after initial design, while the multi-purpose device required human intelligence for re-programming.

An important concept introduced in early-stage analytical machines was *recursion*. A program that once had produced a numerical solution could perform multiple operations on that solution. Babbage called it "eating its tail." In pictures, Escher drew a hand drawing itself (Figure 1.2).

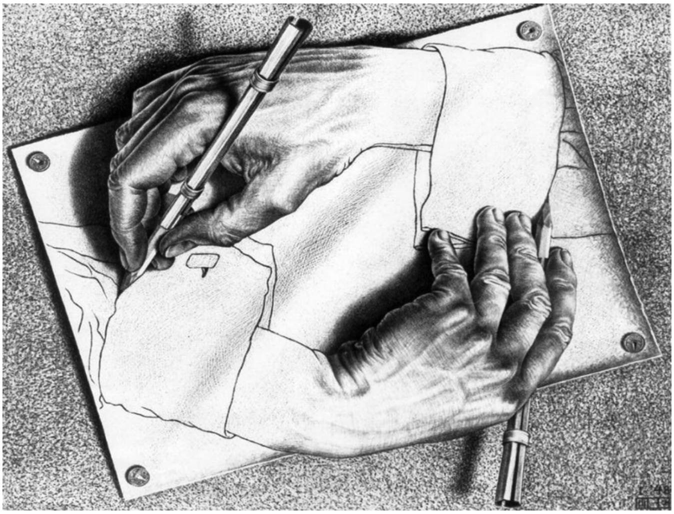

FIGURE 1.2 The concept of recursion. (Drawing Hands, courtesy of M. C. Escher.)

1.1 WHAT MAKES MACHINES INTELLIGENT?

The utility of an intelligent machine is in one sense beside the point. If a technological task can be accomplished that has not been done before, or not done in a specific way, or not done as quickly as before, then it is a worthwhile achievement. The earliest automobiles could not go as far or as fast as a horse, but their mobility was an achievement.

If it is agreed that intelligent machines differ in their degree of intelligence, then the question is how to measure machine intelligence. Blaise Pascal's device did sums and differences. Babbage's analytical machine performed these operations, remembered them, and performed further actions on the results. Babbage's output was more sophisticated in that it was the result of recursive operations and was memorized in print. One way of rating an intelligent machine might be by the utility of the output. However, if we use utility as a measure of machine intelligence, the conclusion will depend on the environment. A waterwheel would be unintelligent in the desert. Ironically, a windmill might still be useful underwater.

Perhaps the lowest level of machine intelligence is a machine that can, once constructed, perform its designed task autonomously. A waterwheel or a stream-fed bowl which never overflowed because of an escape valve might be such examples. Most famously Watt's steam engine governed or regulated its speed by using a rotating arm to shut down the steam feed when the desired speed had been exceeded. Once a machine can have different purposes it has a higher intelligence. This flexibility derives from its ability to react to different programs. A programmable machine is considered partially intelligent since it can have as many purposes as it can have programs. Chronologically, these take the form of replaced barrels in a barrel organ, cards on a Jacquard loom, or a memory storage cog and card system in the Babbage analytical machine. The application of electricity in the twentieth century accelerated these tasks and reduced machine size but did not alter machine structure or concept.

Machines with lower intelligence levels perform assigned tasks and stop when the assignment is completed. More complex assignments can chain tasks or require further action on the achieved purpose (Babbage's "eating its tail"). Although given a general purpose, autonomous machines may use a range of actions to achieve that purpose. If they are autonomous, they will have a way of detecting the environment. Their decision operation is usually a Boolean if-then approach, although Babbage and Lovelace used this approach before it was given this title.

Babbage's first computer was a big step towards intelligent machine. It had input-punched cards, memory storage area, a processing area and output-a bell, and a printer. Although Babbage's machine could perform loop operations on the results of mathematical procedures or "eat its tail," it could not develop new programs, only accept them from an external source.

Following this logic, it could be assumed that an intelligent machine would have a meta-program which would itself be able to create sub-programs for new assignments or contexts. The question of what is an intelligent machine could be rephrased as what makes a person intelligent and how does that person differ from a self-programming machine. This in itself is a moral question.

1.2 THE EVOLUTION OF MACHINE INTELLIGENCE

Computer theoreticians of the last half of the twentieth century discuss computer intelligence as it compares to that of humans. Alan Turing considered a machine intelligent if it could successfully disguise itself as human through words. This human would be prejudiced or act logically within its own point of view, introducing a subjective element in the decision making.

The simple model of evolution in machine intelligence could be borrowed from natural evolution. In the fundamental work *The Phenomenon of Man*, priest and philosopher Pierre Teilhard de Chardin (1959) assumed a level of life essence in inanimate objects which increased with life complexity through plants to simpler and more complex animals to man and eventually angels. He insisted that life was evolving each level to a higher level, so that man would at some point reach the angel level. He also incorporated degrees of self-awareness into this hierarchy. If this model were applied as an analogue for machine intelligence, we could describe low-level intelligent machines as those that once constructed could achieve their single purpose autonomously. A medium-intelligence machine could have its purpose changed by changing its programming (slotted cards, changed barrels in a barrel organ, differing impressions in the wax cylinder of an early phonograph). A higher level machine might have sensory devices to indicate if the environment had changed and if goals had been achieved. At the highest level, the machine would set its own goals.

Unless we are designing intelligent machines to be companions, the quality of the man-machine interface should not be the primary concern. An argument could instead be made for self-determination as the pinnacle of machine intelligence. If a machine could create new programs for novel environments based on its own perceptions, it would be replacing human intervention at each stage.

1.3 MACHINE REASONING

The ability to learn depends on the mode of reasoning, which could be either deductive or inductive. *Deductive reasoning* requires following rules, whereas *inductive reasoning* creates rules from experience. The choice depends mostly on computer memory. A computer with a small memory could accomplish its tasks by following a finite set of rules. The memory store would only need to store these rules. If a task or purpose changed, the memory could be flushed of the old rules and given the required new ones. Such a machine would still be intelligent and able to accomplish its task. It would not, however, be a learning machine and would not be able to evolve in its procedures or purposes.

A computer with a large memory and fast processor would be able to use recursion (trial and error) to discover what approaches were optimal for each specific purpose or environment. When a new environment or purpose were encountered, the computer could search its memory to discover whether the problem had been previously encountered. If the problem was new, the machine could try the closest previous approximation of the problem and problem solution.

The computer would act inductively if from previous problem solutions it created a pattern that could be stated as a rule. In this case, the computer would start by processing inductively, and then functioning inductively. Recursion could enable a loop of this process so that it would "eat its tail."

An example of deductive reasoning is the programmable logic controller (PLC) or nanocomputer, functioning by rules, not by induction. The learning computer, on the other hand, can use its experience to evolve in rule-setting and problem-solving processes, but it will require a larger memory.

Memory storage can be off-site if required. The VIC-20 personal computer had 3.5k usable memory. Large programs could be run despite this by accessing data when needed from attached tape drives. The Atari 2600 game machine also had a very small memory. Extra memory was stored in either inserted game cartridges or from attached tape drives. Perhaps a very small computer with small memory could learn with the aid of access to external memory.

Deductive machines, though, do not need access to large memory, either internal or external. Inductive machines will need large memory to store the results of trial and error in order to create rules as a result of learning.

1.4 MACHINE LEARNING

Learning is a required mode for an increase the level of intelligence. Machine learning implies different learning strategies, based on inductive reasoning. Learning of new rules could be achieved in two modes: either supervised or unsupervised. In *supervised learning*, the output datasets are provided to train the machine and get the desired outputs; in unsupervised learning, no datasets are provided, instead the data are clustered into different classes. Supervised learning problems are categorized into *regression* and *classification* problems. In a regression problem, we are trying to predict results within a continuous output, meaning that we are trying to map input variables to some continuous function. In a classification problem, we are instead trying to predict results in a discrete output. In other words, we are trying to map input variables into discrete categories.

The subjective element in supervised learning could be reduced by introducing expert systems, generalizing information and choices that the interviewed expert(s) is aware of. It could be argued that at least in the subject matter field for which the expert was examined, the system would be indistinguishable from that person. However, this system would be a closer approximation of a fully intelligent machine.

In *unsupervised learning*, if the machine learns by trial and error, then a large memory storage capacity will allow all decisions to be based on pattern matching. Unsupervised learning is using algorithms of clustering data with Principal Component Analysis (PCA), Average Linkage Method (ALM), Self-Organising Maps (SOM), and so on. Does the current situation match a situation previously encountered? If yes, then the action found in memory can be used again. An intelligent machine could, instead of searching its memory, ask if the current situation matched a rule. The rule could be specific, such as whether a temperature is achieved, or broader, such as whether an optimal solution is achieved.

1.5 SOCIETAL IMPLICATIONS OF INTELLIGENT MACHINES

There are societal implications of intelligent machines. The first intelligent Jacquard's loom machine increased unemployment in the weaving industry. Workers correctly assumed that the loom's greater efficiency would reduce the number of laborers required. The Jacquard loom was condemned not because it was intelligent, but because it was more efficient, a part of the Industrial Revolution that would lead twenty years later to the Luddite riots in England. Automation today is seen by many as source of job loss. It has been alternately argued that industrial automation reduces the physical pain and injury caused by the eliminated jobs.

On the other hand, during World War II, Turing led the British team that developed the computer-aided tool for deciphering of German military codes, which may have shortened the war. Nowadays, the level of artificial intelligence of military systems is a significant factor of military balance control. Intelligent machines showed themselves extremely useful in exploration of outer space and solar system.

1.6 ETHICAL IMPLICATIONS OF INTELLIGENT MACHINES

Ethical issues are of primary concern if the intelligent machine is designed to be a human companion. Some examples of intelligent machines, where the quality of the man-machine interface is the major determinant, include health-care robots, military robots, and autonomous vehicles. Their functioning could encounter multiple ethical dilemmas, which are difficult to formalize in a rigorous mathematical sense.

A discussion of machine ethics could be considered to be anthropomorphic. If ethical behavior implies a set of moral rules to be followed, then only a human can be considered to have morality. In that sense neither animals nor machines have ethical behavior. Isaac Azimov (1950) suggested a set of robot rules, which essentially stated that robots could not harm humans. It could be argued that a computer could be programmed to obey these rules or any other morality set. Alternatively, Arthur Clark (1968) imagined a computer, HAL 9000, which by acting through self-preservation could harm humans. An ethical machine would have a software governor that, while allowing it to perform individual assigned tasks, would *keep in mind* the greater good as a limiter.

If ethics is the overriding principle that guides individual actions, then animals and humans can be considered to follow ethical behavior. These behaviors are goal or purpose related. Animal goals in the macro sense tend to be innate. Biologists consider animal purpose to be perpetuation of the species. Individual animal survival is a subset of this aim. While biologists also apply this rule to humans, theologians argue for a Creator-human relationship establishment. Humanists might state that human purpose is self-actualization. The Jesuit philosopher Chardin attempted to blend these three points of view.

In the world of non-intelligent machines, usually it is the external operator who would make ethical decisions for machines that achieve their goal and then stop. If it is the car driver, decisions are made based on the situation, experience, and common ethical principles. If it is an autonomous self-driving car, people crossing a road could be recognized too late for the car brakes to prevent a collision. In this situation, the car intelligence is limited to the least bad solution. For example, it could select to injure the driver by driving off the road so that the larger number of pedestrians would be safe. The if-then question here is what the greater common human good is. If there were more passengers than pedestrians, then the car would aim for the pedestrians. This is ethically an Azimov car. If it were an Arthur Clark car and was ruled by self-preservation, it would ask what would do the least damage to the car, not the humans.

Autonomous cars are the near future. Machine ethics governors will have to be installed. Military drones are the present. If they carry weapons and not simply cameras, we must assume machine ethics have been considered. So far as we know, at all times a human monitors and controls these drones except when the man-machine connection is lost. Most drones have a set of instructions that take over when this autonomous mode is reached. They may be commanded to remain in place or return to base. We have not been told that the default is to continue the attack.

So far as we know the ethical imperative of autonomous cars, outside of war, would be to not harm humans. The ethics of a military drone could be to not harm the humans who own the drone, but to damage humans targeted in the instructions.

This assumes military drones partially agree with Azimov: humans should not be harmed. If they are Arthur Clark drones, they will ask what is best for themselves. While they may drop bombs, they will not commit to a suicidal dive on the target. This kind of decision-making would be absurd from the human point of view, but might happen if self-preservation is included in the drone's set of rules.

The concern with the appearance of autonomous intelligent machines is what kinds of rules will be included in the machine commands that will insist on ethical behaviors when the machine creator is not present. A concern about the ethical commands will be whether intentionally or inadvertently the machine acts to not harm humans or from the point of view of self-preservation. Ideally, self-driving cars either need a memory of all possible driving circumstances from which to choose, or a way of composing new programs for unforeseen circumstances.

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2 Computer-Aided Control in Drying

Alex Martynenko

CONTENTS

Computer-aided control is becoming popular in the food industry because of the multiple benefits offered by computers, including remote access, extended functionality, and the ability to collect and organize information flow and databases. These features are quite important for scheduling of complex operations and process traceability. Computer-aided control in drying is particularly important because of nonuniformity, nonstationarity, and sometimes significant uncertainty of a drying process. In many cases, drying is targeting several objectives, such as maximization of food quality and minimization of production cost, which requires multi-objective optimization.

Computer control could be used on different levels: from the control of single dryers to the control of production lines. Menshutina and Kudra (2001) discussed the range of problems to be solved by computer control with different objectives:

Apparatus level: Control of drying conditions (temperature, humidity, airflow, product flow) with respect to recommendations on a drying process. At this level, computer-aided control is applied to actuators with the objective of maintaining or changing drying conditions according to the particular drying schedule. One of the functions of computer-aided control at this level is fault detection.

Process level: Computers are required for mathematical modeling, process simulation, and statistical analysis. At this level, transport phenomena and material physicochemical properties are considered. The objective is optimization of a given drying process in terms of drying rate, energy consumption, and product quality. The major tools to achieve this goal are models providing both static and dynamic (trajectory) optimization. The recent trend in research publications shows that mathematical and statistical models, mostly used in the past century, are gradually being substituted by more advanced evolutionary, neural networks and fuzzy logic models. Accordingly, simple sensory signals are substituted rather with information flows. Sensor fusion and processing of information require computational power of modern computers both as process observers and controllers. However, the principles of process control are still the same: feedback, feedforward, and adaptive control. Intelligent control is basically either one or a combination of these traditional control techniques.

Process monitoring: It is another computer-aided tool used for better traceability or knowledge accumulation. In the latter case it could be combined with machine learning (supervised or unsupervised). The combination of soft sensors, machine learning, and decision-making framework would constitute *intelligent* computer-aided control, applied not only for compete process automation but also for process optimization with respect to multiple criteria.

Production level: The objective of this level is product consistency, resource management, and full automation of the production line. Therefore, computer-aided control at this level is mostly used for automated inspection, classification, and quality control. This computer control could optimize production logistics including production cycle planning, scheduling, transportation, and so on. The optimization at this level is based on micro- and macroeconomic analysis and often requires remote access to databases and other computer networks.

This chapter is focused on using computer-aided control for drying process improvement. Computer-aided control requires appropriate sensors/instrumentation to make process observable and actuators to make process controllable. In both cases, interfacing computer with peripheral devices and sometimes remote access to data are becoming critical. The equally important aspect, which makes computer-aided control unbeatable as compared to programmable logic controllers (PLCs), is the universal and flexible computer software, already predeveloped for control applications. Computer software for real-time data mining, modeling, and knowledge development has a great potential for the improvement of control strategies and process optimization. Integration of soft computing with machine learning opens new horizons for computer-aided control applications in drying.

2.1 SENSORS AND INSTRUMENTATION

Sensors are mechanical or electronic devices, modules, or subsystems with the purpose to measure changes in environment and send information to a PLC or computer. Sensors usually resemble human senses, such as vision, hearing, smell, touch, taste; however, they go far beyond human sensibility in terms of numeric and repeatable evaluation of environmental variables, such as temperature, humidity, air velocity, and so on. To reflect physical changes in environment, sensors use different physical effects, like the Seebeck effect in thermocouples or the Fourier cooling effect in hot-wire anemometers.

An excellent review of sensors' basic physical principles is presented in *Chemical Engineering* (Anonymous, 1969). The critical characteristics of a good sensor are *sensitivity* (it is sensitive to the measured property); *selectivity* (insensitive to any other property likely to be encountered in its application); and *noninvasive* (does not influence the measured property). On the top of this, the choice of the sensor is determined by its reliability, lifetime, dimensions, inertia, output (analog or digital), accuracy, linearity, offset, range of measurements, cost, and so on.

For linear sensors, the sensitivity is defined as the ratio between the output signal and measured property. For example, if a thermocouple sensor measures temperature and has a voltage output, the sensitivity has units [V/K]. For nonlinear sensors the sensitivity is not constant within the range of measurements. For example, a thermistor with nonlinear transfer function requires calibration for the particular range of measured temperatures.

Accuracy of the sensor is limited by systematic and random error. Systematic error is possible to compensate due to the calibration or signal conditioning. Random error is determined by the sensor's *resolution* or the smallest detectable change in the measured property. The resolution of an analog sensor is determined by signal-to-noise ratio and potentially could be improved by filtering. In contrast, the resolution of a digital sensor is determined only by the resolution of the digital output.

Chemical sensors and biosensors constitute a special class of sensors providing information about the chemical composition of its environment. Such sensors use cells, proteins, nucleic acid, or biomimetic polymers as primary sensitive elements. Their response is converted in electrical signal by transducer (usually semiconductor).

Soft (*or software*) *sensors* are essentially virtual sensors combining nonlinear (and sometimes nonselective) physical sensors with mathematical models for linear transformation and further use in the system observers. Mathematical model and sensor fusion (if necessary) are considered the key elements of the soft sensor.

Instrumentation is a collective term for measuring instruments used for indicating, direct reading, and recording of measured quantities. The term instrumentation may refer to a device or group of devices used for direct reading, or when using many sensors, may become part of a complex industrial control system (De Sa, 2001). It should be noted that instrumentation for computer-aided control systems includes only analog or digital sensors, which are capable of producing a *real-time data stream*. In this case dynamic properties of sensors, such as inertia and time delay become critical for control.

Drying process could be batch or continuous, lumped or distributed. Each case requires careful choice of sensors and instrumentation for the system observer. The old school of drying presumed only observation and control of environmental variables (temperature, humidity, air velocity), without consideration of product quality (Figure 2.1). It did not assume any observability of product.

In contrast, the new school of drying (Su et al., 2015) considers product quality a central concept in drying. The new generation of *smart* drying technologies requires advanced instrumentation for observation of product quality attributes (moisture content, shrinkage, color, texture, physicochemical properties, etc.) and their changes, induced by a particular combination of drying factors. This special class of sensors and instrumentation, reflecting key quality attributes of the product and their changes during drying, includes biomimetic sensors (e-nose, e-tongue), computer vision, and spectroscopy. Computer vision and biomimetic sensors give information about customer-perceived quality attributes, while spectroscopy mostly reflects nutritional and nutraceutical value of the product.

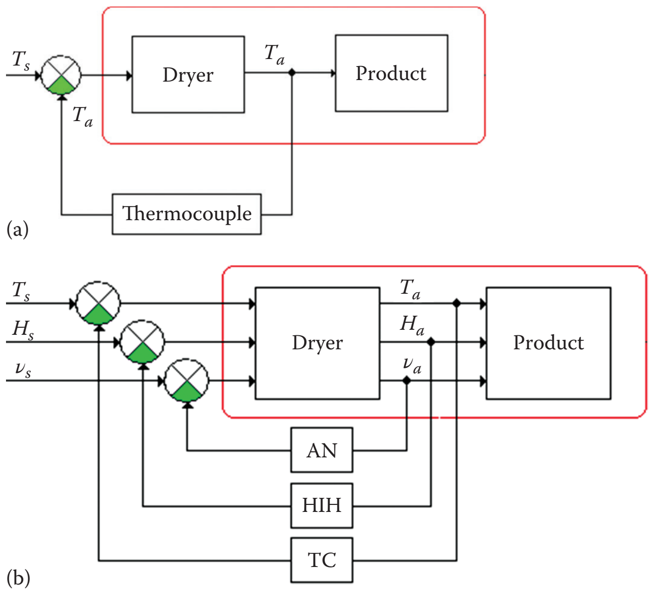

FIGURE 2.1 One-loop (a) and multiple-loop (b) feedback controllers of drying environment: T—temperature, H—humidity, v—air velocity, AN—anemometer, HIH—humidity sensor, TC—thermocouple. Subscripts: a = air, s = set point.

2.2 BIOMIMETIC SENSORS

These sensors measure smell and taste, which affect customer perception of quality and market value of food product. Aroma monitoring is critical for multiple food unit operations, such as sorting, drying, packaging, and storage. In combination with computer software and data analysis, these sensing systems provide cost-efficient real-time solutions for process control and optimization. They replace expensive analytical assays in complex analyses of quality and authenticity of foods. E-noses usually consist of the array metal-oxide semiconductors, selectively sensitive to particular group of aroma components. There are a number of e-noses, available on the market, for example zNose™ (Electronic Sensor Technology, CA, USA), EOS 835 or EOS 507 or MultiNose (SACMI, Imola, Italy), or TGS (Figaro, IL, USA). The zNose was successfully used for aroma monitoring during apple and carrot drying (Raghavan et al., 2010). The information about concentration of aroma components in the drying chamber was used to control the microwave drying process. Although biomimetic sensors are not ideally selective and robust, the number of their applications in drying keeps on growing.

2.3 COMPUTER VISION

The range of applications of computer vision for product inspection, monitoring, and control in the drying industry is increasing exponentially. The first applications of computer vision in food processing focused mostly on relationships between visual appearance of foods and quality attributes. Real-time computer vision as an *intelligent* observer makes it an excellent tool for feedback control of drying. All computer-vision applications could be divided into two categories depending on whether the information was obtained from analysis of individual images or from scrutinizing changes in sequential images. Examples of information from individual images include morphological features (size, shape, surface area, roundness, etc.), color, and texture. These are more *product-related attributes* and can be obtained by morphological and color image processing. The value of time-series imaging was first recognized by Watano and Miyanami (1995) and Saadevandi and Turton (1998) in the powder drying industry. They and their followers discovered important *process-related* information, concealed in sequential images, including particle velocity, acceleration, and material flow pattern. This was the first step to feedback control of the granulation process (Watano, 2001). The first application of time-series imaging for temperature control in convective drying was related to ginseng drying (Martynenko, 2006). This study revealed ability of time-series imaging to identify critical control points in quality degradation. This concept opened the door for the implementation of different control strategies, for example multi-stage control of air temperature with respect to moisture content (Martynenko, 2006), shrinkage (Davidson et al., 2009), product surface temperature (Sturm et al., 2014; Nadian et al., 2016), or even dynamic optimization of the drying process with respect to quality (Martynenko and Yang, 2007). Surprisingly, the number of applications of computer vision for intelligent control of drying is very limited.

Probably, it can be explained by the interdisciplinary nature of this research, which requires basic knowledge of drying principles, image analysis, computer interfacing, and process automation.

2.4 SPECTROSCOPY

Near-infrared reflectance (NIR) spectroscopy in the range of 780–2500 nm is used to identify molecules containing CH, OH, and NH chemical bonds. The NIR spectroscopy technique was employed to estimate moisture content of powder during granulation process in a fluidized bed dryer (De Beer et al., 2011). NIR spectroscopy was also used in the intelligent control system of sausage drying for in-line determination of product water activity (Stawczyk et al., 2004). The potential of NIR for online monitoring of acrylamide, moisture, and oil content was investigated by Pedreschi et al. (2010), who showed high sensitivity of NIR technique to acrylamide content. Hyperspectral imaging employing both the NIR and visible spectrum has been used to identify chemical composition of foods.

Nuclear magnetic resonance (NMR) is another spectroscopic technique, used to identify molecular structures containing hydrogen. Therefore, it is widely used for study of water distribution and transport processes during drying of plant- and animal-based foods. Potential applications of NMR for compositional and structural analyses online in food processing was thoroughly discussed by Marcone et al. (2013).

Microwave dielectric spectroscopy is based on the ability of water to absorb electromagnetic energy in the range from 300 MHz to 300 GHz. This technique appears to be highly sensitive in the range of low moisture contents close to the end point of a drying process. Other advantages are that it allows for measurements of volumetric moisture content independent of density, porosity, and surface properties of solids; does not require sample withdrawal; and provides online data stream. Due to these advantages, microwave dielectric spectroscopy was successfully applied to study osmotic dehydration of apples and kiwifruits, as well as meat products (Su et al., 2015).

Low-power ultrasound (LPU) is recognized as an informative technique for studying and monitoring of physicochemical and structural properties of liquid foods (Awad et al., 2012). It utilizes the phenomena of transmission or reflection of ultrasound waves, which reflect physicochemical properties of food materials, such as microstructure, phase composition, bulk viscosity, and rheology. Pulse-echo and continuous wave ultrasound are two major techniques used in most ultrasound sensors. The LPU technique was successfully used for studying the percentages of meat, fat, muscles, and carcass in animal-based products because they have different acoustic properties. It was also used to estimate the composition of moisture, protein, and fat in fish and poultry products.

Electrostatic sensors (ES) quantify charge, resulting from triboelectric properties of food materials that depend on moisture content, size, surface roughness, composition, and other physicochemical properties. This technique is mostly used in the powder industry (Zhang and Yan, 2003; Rahmat et al., 2011). The ES have several benefits for commercial-scale applications, such as low cost and temperature tolerance; however, the sensitivity of this technique to low moisture contents limits applications to control of only the final period of drying.

It could be concluded that biomimetic, spectroscopic, and electrostatic sensors are promising *soft sensors* for real-time control and automation, however, their commercial applications require more research and development efforts.

2.5 CONTROL AND AUTOMATION

Traditionally, the objective of control in drying is to maintain environmental conditions as close as possible to pre-determined set points, compensating for possible deviations. In most cases, the target output is final moisture content, and performance of control is determined by variation in the final moisture content. Computer-aided control could be applied to the drying environment (conventional control) or to the product under drying to achieve desirable changes (intelligent or *smart* control). The structure of universal computer-aided control, using two feedback loops from process and product, is given in Figure 2.2.

Computer-aided systems include two distinct parts: the controller and observer. The observer collects information about process variables and corresponding changes in product quality, while the controller is adjusting process conditions to achieve desirable product quality. These two are interconnected. The computer-aided observer is adaptive with the ability to correlate product quality attributes with process variables in the form of regression models. The computer-aided controller uses the same inversed models for optimal control of the drying environment. Set points for process and product are specified as a part of the computer-aided drying program.

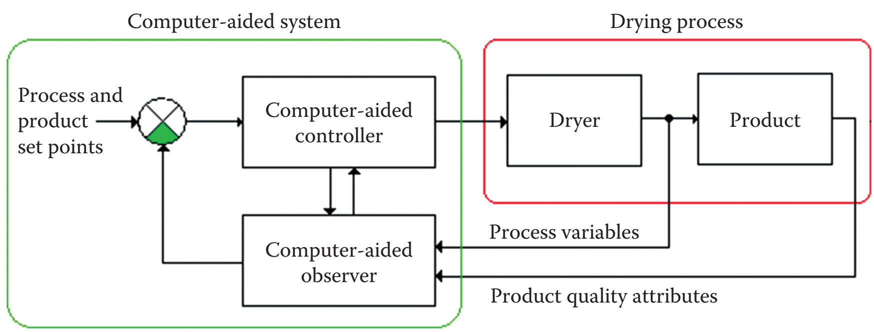

FIGURE 2.2 The structure of intelligent control, focused on product quality.

2.6 CONTROL OF DRYING ENVIRONMENT

Applications of computer-aided control to the drying environment are typical for drying of heat-sensitive biomaterials, like foods and probiotics (Dufour, 2006), where accurate control of drying conditions is critical for the end-product quality. So far, computer-aided control has been successfully applied for the variety of drying processes, such as conveyor-belt drying (Tussolini et al., 2014; Lutfy et al., 2015), fluidized-bed drying (Siettos et al., 1999; Aghbashlo et al., 2014), freeze drying (Pisano et al., 2013), crossflow drying (Li et al., 2008), infrared drying (Dhib, 2007), microwave drying (Hu et al., 2017), rotary drying (Thibault and Duchesne, 2004; Wang et al., 2015), and spray drying (Menshutina et al., 2010). The common goal of these applications is to improve accuracy of fast drying processes. Computer-aided control of the drying environment uses feedback and feedforward control, employing ON/OFF, a proportional-integral-derivative (PID), or neuro-fuzzy algorithms. It makes the drying system more robust, accurate, relatively inexpensive, and scalable for laboratory, pilot, and industrial operations, and therefore it has been widely adopted by industry. For example, Centre for the Analysis and Dissemination of Demonstrated Energy Technologies (CADDET) is considering computer-aided control as the most promising tool for energy-saving solutions in the drying industry. Another example is the Drycontrol™ control system, developed by GEA (Soeborg, Denmark) for spray drying. This system uses model predictive control (MPC) to maintain drying conditions close to their optimal values (Pisecky, 2012). Another application is Dryspec™ 2000, developed for wood drying (Dandoroff and Riley, 2000). Nowadays, most industrial dryers are equipped with less or more sophisticated automatic controllers, which can provide stable and highly accurate control of major drying factors. Availability of process models extended functionality of the computer-aided control to artificial intelligence techniques, such as neural networks, fuzzy logic, and evolutionary algorithms. These models are able to manage nonlinearity, however, they are not able to produce an exact solution for a given problem and do not provide a required flexibility in conditions of uncertainty or system disturbances. Adaptive and self-tuning control systems seem to be a more flexible solution since they are open for supervised and unsupervised learning. However, the obvious deficiency of computer-aided control of the drying environment is that it provides only information about performance of the dryer, but not about the quality attributes of fresh and semi-dried food inside the dryer.

2.7 CONTROL OF PRODUCT UNDER DRYING

The goal of any drying process is to achieve desirable quality attributes (moisture content, size, color, texture) of dry product. With the quality parameters monitored by smart sensors (e-nose, e-tongue, machine vision, or spectroscopy), the control system becomes sensitive to changes of food quality. Consequently, the control system would be able to adjust operating parameters with respect to product quality and the overall objective of the drying process would be to keep the product within stringent quality specifications. Control of product under drying would require a special class of sensors and instrumentation, reflecting key quality attributes of the product and their changes during drying. Some of these sensors have been previously discussed. Computer vision and biomimetic sensors give information about customer-perceived quality attributes, whereas spectroscopy mostly reflects nutritional and nutraceutical values of the product. These sensors, combined with computer software, become a part of *intelligent* computer-aided observer (Figure 2.2). However, embedding these sensors in a drying process as a part of drying system and interfacing with computer requires careful research and engineering.

2.8 COMPUTER INTERFACE

Computer interface is a shared boundary across which two or more separate components of a computer system exchange information. This exchange can take place between software, computer hardware, peripheral devices, humans, and combinations of these. The interface can feature one-way or two-way communication. For example, some computer hardware devices, such as a touchscreen, can both send and receive data through the interface, whereas the others, such as a mouse or keyboard, can only provide an interface to send data to a computer. To process a data stream, computers usually are equipped with digital (parallel or serial) ports. To be used by a computer, analog signals need to be digitized by an analog-to-digital (AD) converter and transferred to the computer using standard communication protocol (RS-232, USB, IEEE-1394, Ethernet, etc.). This functionality is provided by computer interface, compatible with computer software (MS-DOS, Microsoft, MacOS, Linux, etc.).

A communication protocol is a system of rules that allow transmission of information from a computer to peripheral devices and vice versa. The protocol defines the rules syntax, semantics, and synchronization, and possible error recovery methods. The rules can be expressed by algorithms and data structures. Communication protocols are specific for interface, such as serial, parallel, wireless, mobile, and remote (Internet). For example, Internet protocols could include Transmission Control Protocol (TCP), Internet Control Message Protocol (ICMP), Hypertext Transfer Protocol (HTTP), Post Office Protocol (POP), Simple Mail Transfer Protocol (SMTP), File Transfer Protocol (FTP), and many others. The best-known framework is the TCP/IP protocol, which provides transmission of information from/to defined IP addresses. A good example of remote control is a sausage dryer installed in Spain but operated from Poland (Stawczyk et al., 2004). Low-level communication protocols used to exchange information between computer and instrumentation/control devices are called *drivers*.

2.9 SOFTWARE FOR CONTROL APPLICATIONS

Most applications for real-time control of drying operations use MATLAB software (MathWorks, USA). This software is very attractive for computer-aided control and automation due to its extended functionality (Chin, 2017). The set of prebuilt functions and reduction techniques available in MATLAB allows development of predictive models that best capture the predictive power of datasets. These models will allow meaningful interpretation of relationships between inputs and outputs, which will add to our knowledge of the factorial effects on food quality. Also, MATLAB could be used to build kinetic models that predict future outcomes based on historical data. This approach enables efficient exploration of optimal drying conditions and optimization domain. Another advantage of MATLAB software is that it contains multiple toolboxes, such as the Neural Network and Fuzzy Logic Toolboxes to develop inference models, and the Statistics and Machine Learning Toolbox for supervised and unsupervised parametric identification. Supervised learning techniques include ANN training with the Levenberg-Marquardt backpropagation algorithm, whereas unsupervised learning utilizes the Self-Organized Maps algorithm. Inference and mathematical models are the key parts of the adaptive control system, serving as a part component of *intelligent* observers. Optimization of drying conditions with respect to quality could be done by using MATLAB Optimization Toolbox. In this case, the drying process is considered as a nonlinear programming problem, which could be solved using a gradient-based dynamic optimization solver, available in the MATLAB software. It significantly simplifies the decision-making framework to dynamic optimization strategy, generating optimal solutions for each time point. An additional advantage of using MATLAB is that this software package already contains a Computer Vision System Toolbox and Image Processing Toolbox, which are instrumental for real-time quality (color, texture, and microstructure) evaluation. Using the set of quality attributes, measured in real time, the goal of control is to find maximum and/or minimum of objective function over constrained domain. This is illustrated by example of ginseng drying (Martynenko and Yang, 2007). MATLAB software also includes the Simulink package, which is suitable for modeling, simulation, and analyzing behavior of dynamic systems. Simulink enables systematic verification and validation of models in real time on the physical system. Also, Simulink contains advanced graphical interface and is widely used for automatic control and digital signal processing. However, MATLAB does not allow simultaneous real-time data acquisition, processing, and control.

In contrast, LabVIEW (National Instruments, Austin, TX, USA) sufficiently combines all three functions in real time, enabling computer-aided control of drying. For advanced control, LabVIEW has a special Data Acquisition and Control software package, developed for real-world applications. The major benefit of this software is the concept of two-ways signal acquisition and signal generating. Widely developed PCI or USB computer interface enables real-time communication with multiple physical sensors (temperature, sound, vibration, strain, pressure, force, position, imaging devices, etc.) and actuators. Image acquisition and processing with LabVIEW software was successfully used by Martynenko (2008) and Davidson et al. (2009) for multi-stage temperature control in ginseng drying. An example of computer-aided observer of quality attributes (color and shrinkage) is shown in Figure 2.3.

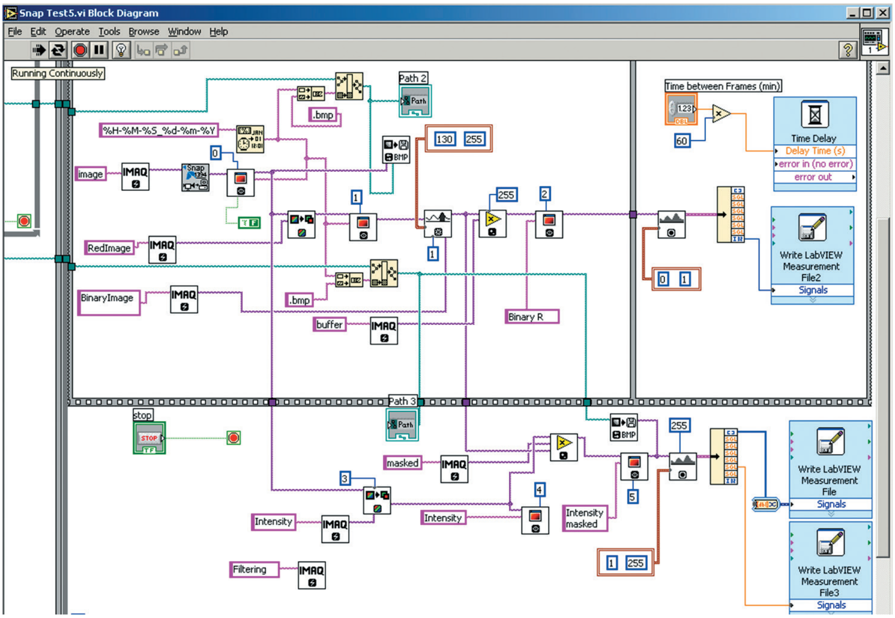

FIGURE 2.3 LabVIEW code for intelligent observer of color and shrinkage from real-time imaging.

An additional benefit of LabVIEW software is its open architecture, allowing MATLAB and C++ codes to be embedded into the processing algorithm. The combination of two powerful software packages would be able to compensate perceived deficiencies of control applications.

2.10 EXAMPLE OF COMPUTER-AIDED CONTROL FOR GINSENG DRYING

Structural synthesis of computer-aided control system is illustrated with the example of ginseng root drying (Martynenko and Yang, 2007). The objective function J was defined as the negative value of root final quality (loss function) and minimization of this criterion is performed

$$J = -Q(t_e) \tag{2.1}$$

$$\min_{T(\tau),\ \tau\in[0,t_e]} J$$

Target value for the final moisture content is specified as a constraint:

$$m(t_e) = m_e \tag{2.2}$$

The control variable (temperature) was constrained to the range of technological limits:

$$T_{\min} \leq T(t) \leq T_{\max} \tag{2.3}$$

where $T_{\min} = 38°C$, $T_{\max} = 50°C$ are technological limits for ginseng roots drying.

An auxiliary optimization criterion (J_{aux}) was used to obtain feasible (but generally suboptimal with respect to the quality) control:

$$J_{\text{aux}} = \left(m(t_e) - m_e\right)^2$$
$$\min_{T(\tau),\, \tau\in[0,t_e]} J_{\text{aux}} \tag{2.4}$$

Applying the main criterion (J) for quality maximization resulted in a static solution of the optimization problem at the lower safety margin $T(t)$ = 38°C (const.). This control decision is intuitively used in ginseng drying to avoid risk of quality losses. However, the price to pay for this cautious control strategy is reduced performance: it takes about 240 hours to dry ginseng to the target moisture content.

Minimization of drying time is another economic goal. To achieve this goal, the optimization problem was reformulated as searching for the best trajectory of air temperature to reduce the total drying time constrained with the following quality loss function:

$$J = -t(m_e)$$
$$\min_{T(\tau),\, \tau\in[0,t_e]} J \qquad Q \geq Q_{\min} \tag{2.5}$$

It follows that the drying process can easily be started at 50°C, with the next gradual decreasing of temperature in the region of the highest risk of quality degradation (10–50 hours), and then increasing temperature at the end of drying. For example, if quality loss is constrained at the level 0.2, the trajectory of temperature can be determined as:

1. $0 < t < 6$ $\quad T = 50°C$
2. $6 < t < 75$ $\quad T = f(t)$ $\quad$ Trajectory follows the isocline $Q_{\min} = 0.2$
3. $75 < t < 90$ $\quad T = 50°C$

This strategy allowed minimization of drying time to 70–90 hours with guaranteed quality. The optimal compromise between quality and time of drying can be found by running several optimization calculations and constructing the Pareto graph of the highest achievable final quality versus drying time.

Performance of the intelligent control system was tested on a pilot batch dryer. Bulk average moisture content and quality were estimated using machine-vision and neural network estimator. Estimated moisture content was used as a global feedback parameter for the identification of the drying stage and adjustment of the drying conditions according to the specified control objective. Estimated quality was used as another feedback parameter to prevent quality loss below the specified

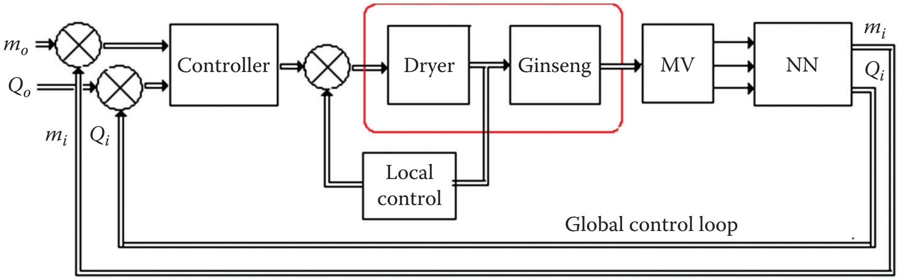

FIGURE 2.4 Structure of intelligent control system for ginseng drying with local and global control loops. (From Martynenko, A.I., and Yang, S.X., Intelligent control system for thermal processing of biomaterials, *IEEE Conference on Networking, Sensing & Control*, London, UK, 93–98, 2007.)

level. Subsequently, the control system consisted of three modules: machine-vision observer, neural network estimator, and controller (Figure 2.4).

Machine vision (MV) generated the set of morphological, textural, and color features as time-independent process variables. This information was used by the neural network (NN) to estimate moisture content and quality (m, Q). Both moisture and quality were used as feedback variables in a global control loop and as constraints in the optimization algorithm. Arranging the data into time series enabled calculation of the drying rate factor and quality degradation rate in dynamic models. The controller was running in a regime of dynamic optimization, performing calculation of the best trajectory of air temperature with respect to criterion (Equation 2.1) or (Equation 2.4), using sequential optimization routine, available in MATLAB.

The observer and controller were developed as re-configurable LabVIEW applications with an extensive set of functions for image processing, data fusion, calibration, and advanced logic control. Data extracted from image analysis represented both quality factors perceived by consumers (color, texture) and process parameters (diffusivity, rate) important for the development of intelligent control. The results demonstrated the feasibility of an intelligent control system to be used as an accurate tool for a multi-stage ginseng drying (Martynenko, 2006). Based on acceptable risk of quality degradation ($Q_{min} = 0.2$), the controller identified three critical control points in a drying cycle: (1) point for gradual decreasing of drying temperature from 50°C to 38°C; (2) point to turn back from lower 38°C to higher temperature 50°C; and (3) point when moisture content attains the target value (0.1 kg/kg) to stop drying. Optimization of temperature reduced drying time from 240 to 90–110 hours, yet with high product quality.

2.11 FUTURE TRENDS

Based on our review of recent trends in computer-aided control in drying, we could predict future development towards embedding elements of artificial intelligence into drying control systems (Martynenko, 2017). Considering that nonlinear, nonstationary, and nonuniform drying also have high variability in initial conditions, the elements of artificial intelligence could significantly improve quality of control. Observation of previously nonmeasurable quality attributes in real time will resolve the problem of global controllability of both process and product quality. Observation of spatial variation of process and product attributes would enable optimization of control of distributed systems, for example crossflow dryers. In terms of process control, we could predict a shift into non-isothermal drying strategies, based on the changes of product physicochemical properties in the process of drying (Martynenko and Kudra, 2015). Machine learning would simplify research and optimization of drying strategies. In the future we can expect better exchange of information and data through global networks. Combining of common knowledge into the form of global expert systems will simplify development of innovative and hybrid drying technologies, based on underexplored physical phenomena and computer-aided control.

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