Mathematical Programming Based Synthesis of Rice Drying Processes

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Various drying models have been developed in the extent which they are available for the analysis of drying processes in a variety of practical drying systems. However, most were focused only on a single unit operation; mainly the dryer. Nevertheless other unit operations such as cooling and tempering units are also employed in industrial drying systems. Therefore, there is an important need for an integrated analysis of rice drying systems which takes into account all the interactions between the units that appear in a drying process. The aim is to select a process out of the large number of alternatives and operating conditions which meet the specified performance.

In this work, the synthesis problem of drying processes will be thoroughly investigated using various drying models. Both simplified (empirical) and rigorous (theoretical) models were used. The aim is to find the optimum configuration and operating conditions which satisfy two optimization criteria. One is to maximize the quality (head rice yield) and the other is to minimize the energy consumption. To solve the synthesis problem, mathematical programming will be used as a tool. Three major steps involving the application of mathematical programming in synthesis problems were developed and presented; superstructure representation, problem formulation and optimization strategy.

For the synthesis problem using empirical models, the problem was formulated as an MINLP model. However, due to the fact that different mathematical models are often possible for the same synthesis problem and the recent advances in modeling techniques, generalized disjunctive programming (GDP), known as an alternative model to MINLP, was used. The objectives are to investigate the benefit of using GDP as an alternative model to MINLP and also to exploit a disjunction part of a GDP model for integrating alternative choices of empirical drying models to eliminate the problem of having drying models which are valid only in a small range of operating conditions. The results showed that different drying strategies were obtained from using different drying models in the case of maximum head of rice yield (quality) while the same strategies have been found from using different drying models in the case of minimum energy consumption. This finding is due to the reason that quality as an objective function is highly nonlinear; therefore it contains many local solutions while the energy objective function is a simple linear function. In the aspect of using GDP model, we found that GDP models provide good structure of variable relationships which can improve the search

strategy and solution efficiency for the problem dealing with highly nonlinear functions such as in the case of maximum head price yield. Moreover, because of this good characteristic of MINLP based GDP model, the synthesis problem of rice drying processes dealing with various kinds of empirical models can be solved in reasonable time in GAMS. Nonetheless, in the case that the optimization problem is dealing with the simple mathematical function, the GDP model did not outperform the ad hoc MINLP model for the case of minimizing energy consumption. Also, GDP modeling framework facilitated the problem formulation of the synthesis problem which had two drying models valid in a different range of drying operations in rice drying processes.

The synthesis problem using theoretical models arising from the simultaneous heat and mass transfer balances gave rise to a mixed-integer nonlinear programming (MIDO) model. Such problem is highly nonlinear, multimodal and discontinuous in nature and is very difficult to solve. A hybrid method which combines genetic algorithms (GAs) and control vector parameterization (CVP) approach was proposed to solve this problem. In the case of maximum head rice yield, the results of the synthesis problem showed that high quality rice grain can be preserved regardless of the choice of drying configuration as long as the drying process is operated under a condition which produces the least amount of moisture gradient within the rice grain. Many local optimum solutions which gave rise to different drying configurations and operating policies were found from using different initial guesses. In the case of minimum energy consumption, the results showed that a cooling-tempering configuration which operates at ambient temperature gave the minimum energy consumption. Different initial guesses converged to the same drying configuration (cooling-tempering) but different operating policies and total number of passes. Moreover, since the optimal operating time in a cooling unit is at the upper operating bound allowed in this unit, the effect of the bound of operating time for a cooling unit on the total number of passes required was studied. The results showed that less number of passes would be obtained if longer periods of cooling are allowed. The hybrid proposed method was able to solve MIDO problems; albeit at a relatively large computational expense.

For the comparison aspect between the theoretical and empirical models for synthesis of rice drying processes, empirical models are easier to use for the synthesis problem but they are valid only within the range which they were developed. Also, there is a need for developing a model for each particular unit employed in rice drying processes. For the synthesis problem with theoretical models, this problem gives rise to the most difficult class of optimization problems; however, a theoretical model provides a better understanding of the drying kinetics happening in rice grain. Moreover, theoretical models alleviate the need to develop models for each particular unit employed in rice drying systems. The common feature found from using theoretical and empirical models is that head rice yield objective function always gives rise to different choices of drying configurations while the energy objective function always give rise to a unique drying configuration (cooling-tempering).

Different drying strategies have been found from using different drying models. These alternative configurations provide a broader vision on the operation of drying systems. To decide which one is the best, other factors must be taken into account such as investment cost, term of uses and available technology.

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Nomenclature

Sets

i	Disjunctive term in disjunction k
j	Pass number
k	Disjunctive set

Variables

A_w	Water activity
B_{10}	Mass transfer coefficient between the two grain compartments at 0 °C
B_{11}	Sensitivity coefficient of the mass transfer between the two grain compartments
B_{20}	Mass transfer coefficient between the outer grain compartment and the air at 0 °C
B_{21}	Sensitivity coefficient of the mass transfer between the outer grain compartment and the air
c_k	Fixed charges of disjunction k
C_j	Binary variable for an existence of a cooling unit in pass j
C_1	Sensitivity coefficients of the water activity with respect to the moisture content in the outer grain compartment
C_2	Sensitivity coefficients of the water activity with respect to the moisture content in the outer grain compartment
C_3	Sensitivity coefficients of the water activity with respect to the grain temperature
C_4	Sensitivity coefficients of the water activity with respect to the grain temperature
C_5	Constant used in equation (4.9) between heat and mass transfer coefficients
C_{pg}	Specific heat capacity of the dry grain
C_{pw}	Specific heat capacity of water
D_j	Binary variable for an existence of a drying unit in pass j
E	Energy consumption

E_a	Equivalent activation energy for quality degradation kinetic
E_C	Energy consumption for a cooling unit
E_D	Energy consumption for a drying unit
$f'(x)$	Objective function of continuous variables
$f(x,y)$	Objective function
$g'(x)$	General constraints of a GDP model
$g(x,y)$	Inequality constraints
$h'_{ik}(x)$	Equality/inequality constraints of disjunctive term i in disjunction k
$h(x,y)$	Equality constraints
I_k	The number of choices for each disjunction k
k_0	Quality degradation rate coefficient
k_p	Point constraints
k_C	Cooling parameter
k_D	Drying parameter
L	Objective function represented in an integral form
L_v	Specific heat of vaporization
$mCin_j$	Inlet moisture content to a cooling unit in pass j
$mCout_j$	Outlet moisture content from a cooling unit in pass j
$mDin_j$	Inlet moisture content to a drying unit in pass j
$mDout_j$	Outlet moisture content from a drying unit in pass j
$mPin_j$	Inlet moisture content to a tempering unit in pass j
$mPout_j$	Outlet moisture content from a tempering unit in pass j
M_e	Equilibrium moisture content of grain
M_i	Initial moisture content
M_{ik}	Big-M parameter
M_f	Final moisture content

Min_j	Inlet moisture content to pass j
$Mout_j$	Inlet moisture content from pass j
M_t	Moisture content of grain at anytime
$M1_j$	Binary variable for an existence of node *M1* in pass j
$M2_j$	Binary variable for an existence of node *M2* in pass j
$M3_j$	Binary variable for an existence of node *M3* in pass j
$M4_j$	Binary variable for an existence of node *M4* in pass j
MR	Moisture ratio
N	Drying parameter
p_a	Partial vapour pressure in the drying air
p_g	Partial vapour pressure at the grain surface
p_{gsat}	Saturated vapour pressure at the grain temperature
P_j	Binary variable for an existence of a tempering unit in pass j
P_C	Crossover rate
P_{m1}	Inversion mutation rate
P_{m2}	Uniform mutation rate
P_t	Tournament probability
Q	Quality of rice grain measured in a term of head rice yield
r	Random number
R	Perfect gas constant
RH	Relative humidity
RH_D	Relative humidity of drying air
RH_C	Relative humidity of cooling air
$S1_j$	Binary variable for an existence of node *S1* in pass j
$S2_j$	Binary variable for an existence of node *S2* in pass j
$S3_j$	Binary variable for an existence of node *S3* in pass j

$S4_j$	Binary variable for an existence of node *S4* in pass j
S_{sg}	Specific dry grain surface
t	Time
t_C	Cooling time
t_D	Drying time
t_0	Initial time
t_f	Final time
T_a	Air temperature
T_C	Cooling air temperature
T_D	Drying air temperature
T_g	Grain temperature
$u(t)$	Continuous control variables
$v1_j$	Binary variable for an existence of arc *v1* in pass j
$v2_j$	Binary variable for an existence of arc *v2* in pass j
$v3_j$	Binary variable for an existence of arc *v3* in pass j
$v4_j$	Binary variable for an existence of arc *v4* in pass j
$v5_j$	Binary variable for an existence of arc *v5* in pass j
$v6_j$	Binary variable for an existence of arc *v6* in pass j
x	A vector of continuous variables
$x(t)$	Continuous variables describing the state of the dynamic system
$\dot{x}(t)$	Derivative of x with respect to time t
x_1	Grain moisture contents of compartment 1
x_2	Grain moisture contents of compartment 2
$\bar{x}$	Average moisture content of the grain
y	A vector of discrete variables
y_{ik}	Binary variables of disjunctive term i in disjunction k

Y_{ik}	Boolean variables of disjunctive term i in disjunction k
Z	Objective function of a GDP model
v	Continuous time invariant parameters
γ_{ik}	Value of fixed charges for disjunctive term i in disjunction k
v^{ik}	Disaggregated variables for a continuous variable x
λ_{ik}	Binary variables for disaggregated variables
ϕ	Objective function at the final time
β_1	Mass transfer coefficients between the two compartments
β_2	Mass transfer coefficients between the outer compartment and the air
α	Heat transfer coefficient between the grain surface and the drying air
τ_1	Volume fraction of the compartment 1
τ_2	Volume fraction of the compartment 2
ρ_g	Dry rice density
$\Omega(Y)$	Logic propositions

Abbreviations

B&B	Branch and Bound
CP	Complete Discretization
CVP	Control Vector Parameterization
DAE	Differential Algebraic Equation
DO	Dynamic Optimization
GA	Genetic Algorithm
GAMS	General Algebraic Modeling System
GBD	Generalized Bender Decomposition
GDP	Generalized Disjunctive Programming
HRY	Head Rice Yield
IVP	Initial Value Problem
LP	Linear Program
MIDO	Mixed-Integer Dynamic Optimization
MILP	Mixed-Integer Linear Program
MINLP	Mixed-Integer Nonlinear Program
NLP	Nonlinear Program
OA	Outer Approximation
SEN	State Equipment Network
STN	State Task Network

Chapter 1
Introduction

1.1 Introduction

Rice is the second largest produced cereal in the world after wheat. World rice production is significant and is growing steadily due to increasing production in Western and Eastern Asia. At the beginning of the 1990s, annual production was around 350 million tons and by the end of the century it has reached 410 million tons. Production is generally concentrated in Western and Eastern Asia with more than 90 percent of the world output. China and India, which account for more than one-third of the global population supply over half of the world's rice. Brazil is the most important non-Asian producer, followed by the United States. Italy ranks first in Europe as shown in Figure 1.1 (UNCTAD, 2005).

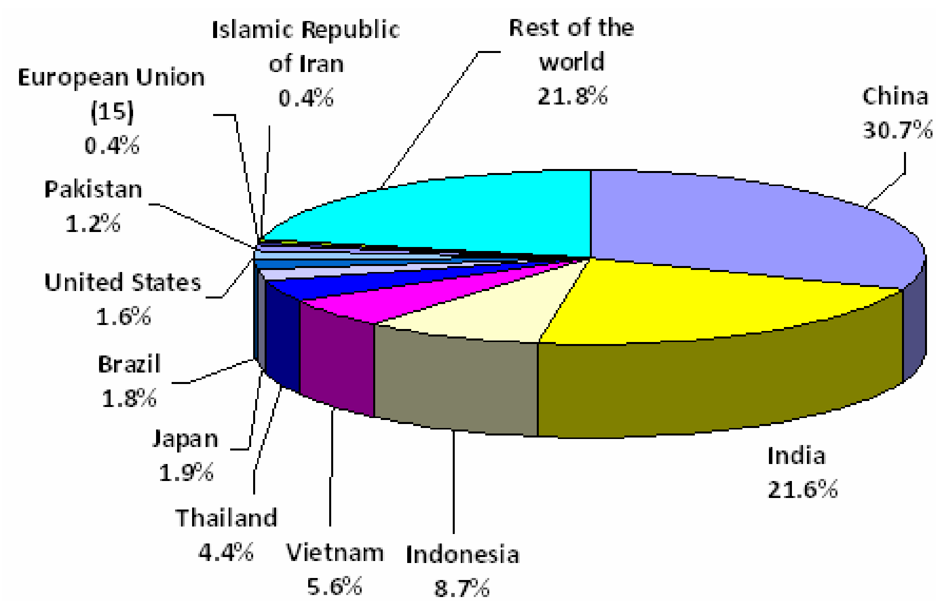


Figure 1.1. Distribution of the world paddy rice production in average of year 1999 to 2003 (UNCTAD, 2005).

Rough rice is a hygroscopic, living and respiring biological material. It is usually harvested at high moisture content ranging from 25 to 40% dry basis (Atthajariyakul and Leephakpreeda, 2006) which has a high respiration rate and is very susceptible to attack by micro-organisms, insects and pests.

Newly harvested grain with high moisture content must be dried within 24 hours to about l4 percent for safe storage. However, drying process has a significant effect on the quality of dried rice due to the reason that its drying characteristics are different from other grains such as wheat, corn and soybeans because it has an outer hull cover and a brown rice (bran + white rice) layer as shown in Figure 1.2. As a result, during the drying process, heat and mass transfer processes occur in each layer of rice grain are different (Noomhorm and Verma, 1986; Brooker et al., 1992) and excessive moisture and temperature gradient will be developed within a rice grain.

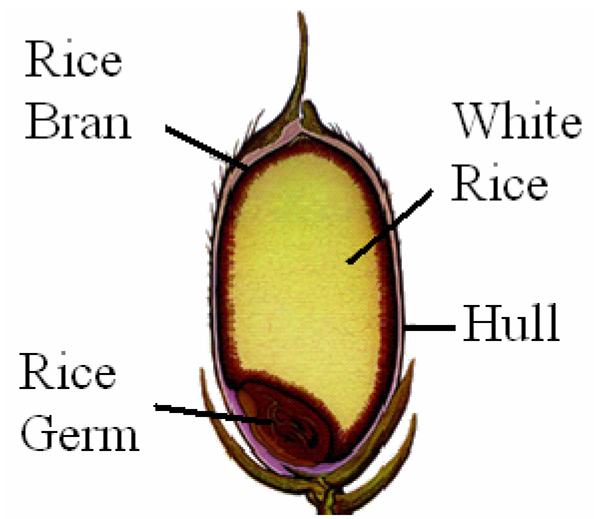


Figure 1.2. Grain structure of rice kernel.

For example, considering the drying characteristic of rice grain in five-pass drying system consisting of a drying and a tempering unit in each pass, the lost moisture content in each compartment versus the drying pass were plotted as shown in Figure 1.3. Moisture content in an individual kernel is lost first from the hull, and then the inner kernel loses moisture to the hull. In the high temperature drying system, the grain was exposed to drying conditions for about half an hour. During this short time, the hull lost four to six percentage points of moisture, but the inner kernel lost only about one point. During tempering (holding the grain in a bin for at least two hours with no drying air flowing through the bin), the inner kernel continued to lose moisture and the hull gained moisture. As a result, continuous loss of moisture from the inner kernel during the repeated drying and tempering cycles occurs when the grains goes through cycles of moisture loss and gain (James, 1998).

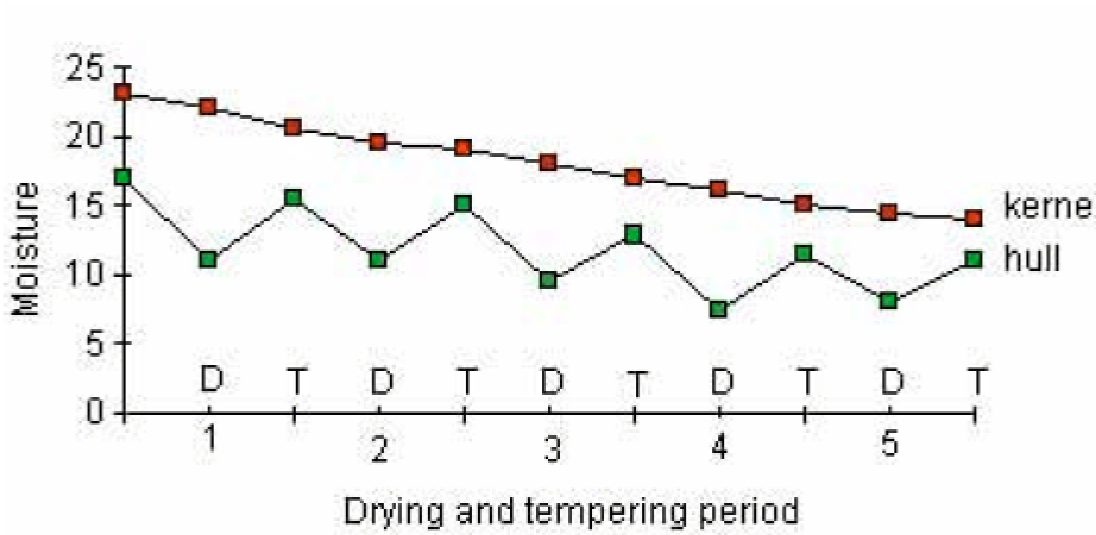


Figure 1.3 Moisture content of kernel and hull after each drying pass in five passes drying of rough rice (James, 1998).

Ezeike and Otten (1981) described that at some point during a high temperature drying process, the rate of moisture removal becomes controlled by the rate of moisture diffusion within the rice grain. By this time, a significant moisture gradient has been developed, and moisture will diffuse to the surface by this gradient, as described by Fick's first law of diffusion.

Improper drying method causes fissuring during the drying process due to excessive moisture and temperature gradients. Fissuring then leads to the breakage of the rice grain in milling processes resulting in the lower yield of head rice. The term "head rice" is normally defined as rice kernel comprised of three-fourth or more of the original length (Olmos et al., 2002). Nevertheless, Aguerre et al. (1986) studied the effect of drying condition (drying temperature, air velocity, and air relative humidity) on the quality of milled rice and they found that temperature gradient alone did not influence the degree of breakage when no moisture loss occurred. Prachayawarakorn et al. (2005) also stated that breakage is a result from the development of stress cracks inside kernels induced by non-uniform distribution of temperature and moisture and this causes the grain to have lower resistance to milling. Thermal stresses usually occur during the heating period and become smaller afterwards while moisture stresses become more important.

Yang et al (2002) determined the moisture content gradients versus drying durations by finite element modeling and found that the head rice yield (HRY) was highly related to the moisture content gradients, which had a maximum value at a drying duration of about 28 min for the rice variety 'Cypress' before declining slowly thereafter, when the rice was thin layer dried at 60^{o}C and 17% relative humidity (RH) from an initial moisture content of 22.1% (w.b).

Moreover, rice is eaten as a whole. The value of rice is directly determined by head rice yield (HRY) so that lower yield of head rice will lower the market value of rice (Beeny and Ngin, 1970). The price received from head rice is approximately twice that the price received from broken rice. Therefore, maintaining high HRY is economically important in rice drying processes (Spadaro et al., 1980). From an industrial point of view, maximizing the proportion of head rice obtained after milling is a first priority (Abud-Archila et al., 2000b).

Apart from the significant effect of drying on quality of rice, drying is an energy intensive process and dominates not only the capital costs but also the operating costs (Barttfeld et al., 2006). The energy needed for a particular dryer or drying system is thermal and mechanical energy. Thermal energy or fuel is used for air heating. Mechanical energy or electricity is due to the operation of the dryer fan, grain conveyors and elevators. The energy requirement in the drying process is normally defined in terms of specific energy which is the sum of the fuel and the electrical energy needed in a particular dryer (or drying system) to evaporate a unit quantity of water. It is usually expressed in megajoules per kilogram of water (MJ/kg). For grain dryers operating in the 50-200^{o}C range, the specific energy requirement can be expected to fall between 3.0 MJ/kg and 10.0 MJ/kg (Brooker et al., 1992).

1.2 Drying method

Due to the reason that each layer of rice grain has different potential in losing moisture content, there is a significant development of moisture gradient within the rice grain which is dried too fast in one pass. Multi-pass drying systems are therefore recommended and employed in rice industries (Brooker et al., 1992).

Walker and Bakker-Arkema (1998) recommended that to prevent the breaking of rice grain, rice has traditionally been dried in three to five stages or passes. In each stage rice passes through the dryer and then is allowed to rest in a bin from 4 to 24 hrs, to allow time for moisture in the kernel to redistribute. Most of the rice crop in the U.S. is dried at commercial drying installations or rice mills in continuous-flow dryers by this multi-pass or multistage method.

In grain drying, the holding of the grain between passes through a multi-pass drier is called tempering. The length of the holding period is called the tempering time. The tempering process refers to the migration of moisture inside the grain which serves to equalize the moisture concentration throughout the grain kernel. A uniform moisture distribution in the kernel increases the drying rate and decreases the internal stress of grain. Moreover, increasing the rate of drying improves energy utilization during the subsequent drying passes for rice. It is important to know the tempering time that is appropriate for a particular set of conditions. If holding period is too short, cracking may occur which will affect the subsequent milling quality of the grain. On the other hand, the tempering period should be as short as possible to minimize damage caused by chemical changes, respiration, insect and microbial activity (Steffe and Singh, 1980).

The most efficient energy utilization (BTU/kg of water removed) during multi-pass drying is achieved if complete tempering (complete moisture equalization) is allowed between drier passes (Steffe and Singh, 1980). Thakur and Gupta (2006b) found that the percentage energy saving by providing 30, 60 and 120 min resting periods was 21.3, 42.7 and 44.0% respectively, in comparison to the energy consumed in continuous drying. Therefore, tempering of paddy during the drying operation has become a common practice for reducing breakage percentage of rice grain. Many research works (Beeny and Ngin, 1970; Harnoy and Radajewski, 1982; Shei and Chen, 1998; Chen and Wu, 2000; Cihan and Ece, 2001; Shei and Chen, 2002; Madamba and Yabes, 2005; Thakur and Gupta, 2006b; Thakur and Gupta, 2006a) have focused on the effect of the combinations of drying strategies (e.g. drying air temperature, relative humidity, drying time) and tempering time on drying rate, quality of rice grain and energy consumption both experimentally and mathematically (simulation).

As discussed earlier, to dry rice from high moisture content to the safe storage level, dryers are not usually the only unit operations employed in a rice drying process. They are normally combined with other unit operations such as cooling and tempering units. Many configurations and designs of rice drying systems have been employed in many countries around the world such as the crossflow dryer shown in Figure 1.4, re-circulating rice dryer shown in Figure 1.5, two-stage concurrent-flow dryer as shown in Figure 1.6 and the multi-pass drying system of drying and tempering units shown in Figure 1.7. Nevertheless, there are three main unit operations involved: drying, cooling and tempering units. Drying units are for removing the moisture content within a rice grain. Cooling or sometimes known as air ventilation units are for cooling down the grain temperature to prevent moisture accumulation on the grain surface as well as removing some amount of moisture content at lower temperature than in a drying unit (Prachayawarakorn et al., 2005) and finally tempering units are for equalizing the moisture gradient developed during the drying processes.

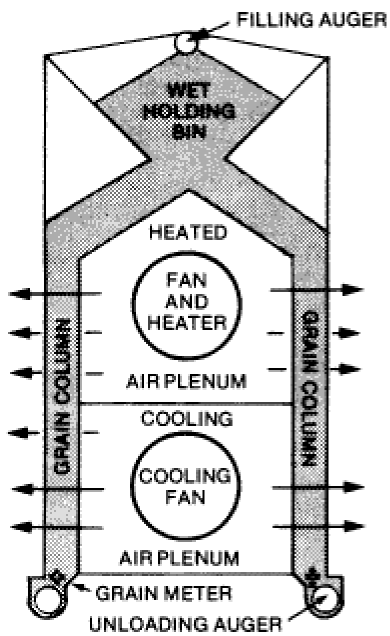


Figure 1.4. Conventional crossflow dryer with a drying and a cooling section (Brooker et al., 1992).

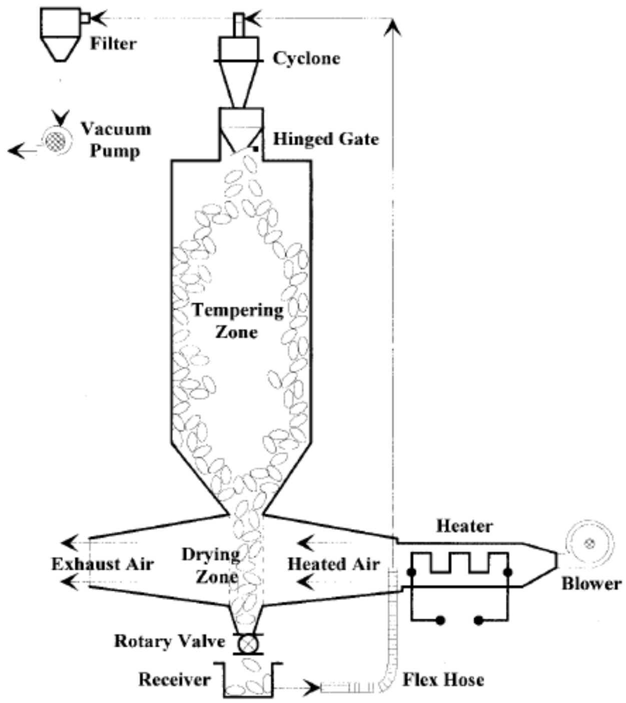


Figure 1.5. Re-circulating rice dryer with a drying and a tempering zone (Shei and Chen, 2002).

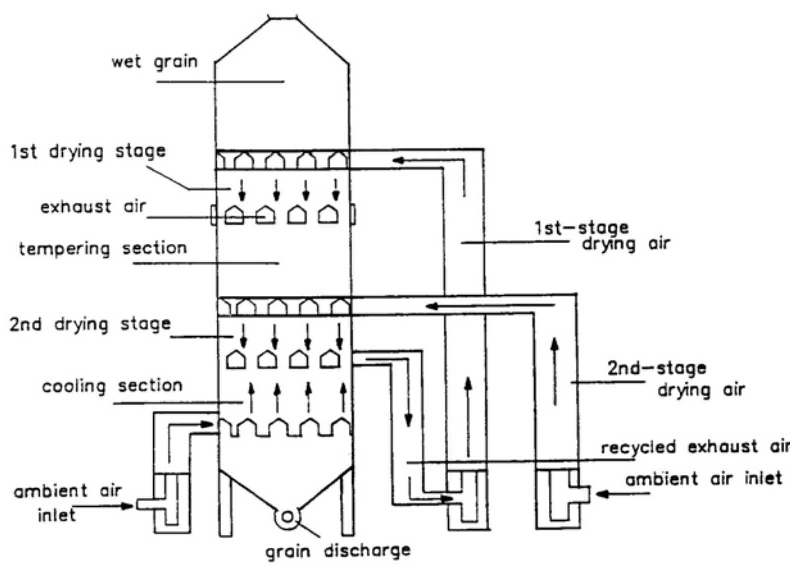
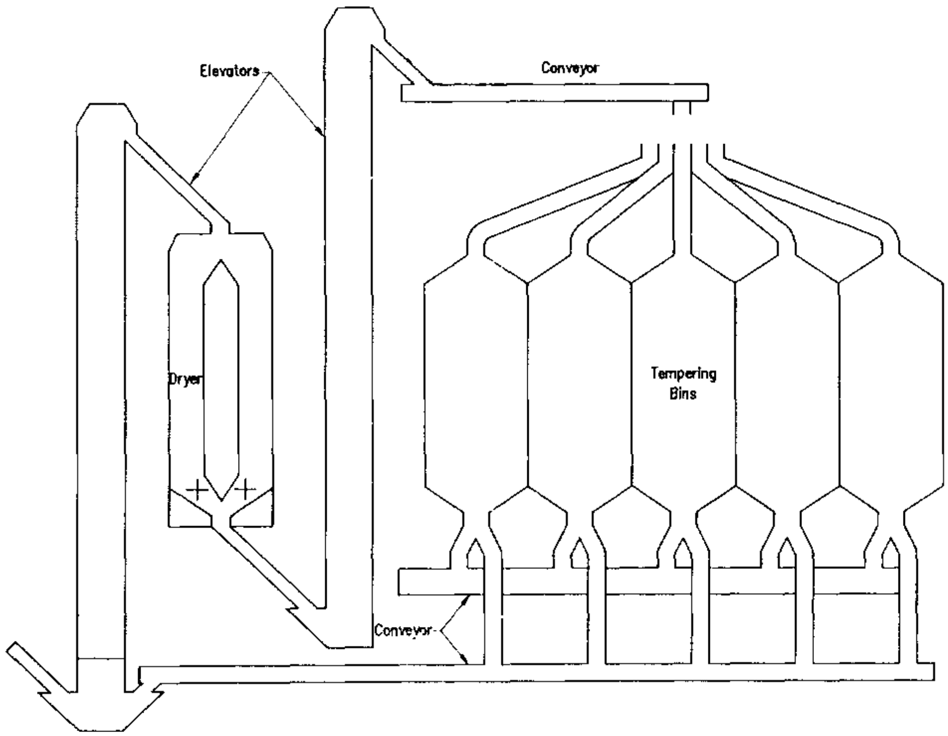


Figure 1.6. Two stage concurrent-flow dryer with counterflow cooler and tempering section (Brooker et al., 1992).



Source: Wimberley (1983).

Figure 1.7. A multi-pass drying system of drying and tempering units (FAO, 1994).

The operating conditions of each drying system vary differently. For example, in the dryeration process introduced by “Foster”, grains are dried at high temperature 60^{o}C to within 2% of the desired final moisture content and transferred to a separate tempering bin. Grains were tempered 6 to 8 hrs with no aeration. This is followed by slow cooling using ambient air at about 0.6 m^{3}/min-ton for 8 to 12 hr (Gunasekaran, 1986).

In the intermittent drying, grains are dried for approximately 3 to 15 minutes in a dryer and then grains are passed to a tempering unit for roughly 40 to 120 minutes. The drying and tempering cycle is repeated until the grain reaches the desired final moisture content (Shei and Chen, 1998).

The traditional tempering/drying procedure for rough rice is based on heating the grains in the drying section of dryer for 8 to 10 minutes, and then grains are sent to the tempering section and stored for the desired period. In the tempering periods, the moisture in the inner layer of grains has enough time to transfer to the outer layer of grains. The recommend tempering period of drying grains with moisture content ranges from 18 to 20% is 2 to 3 hrs(Chen and Wu, 2000).

In the crossflow and mixed-flow drying system, the amount of moisture removed from rice grain per pass should be limited to 1.0-2.0 percentage points (%w.b.) except for the first pass when the rice grain is relatively high in moisture content 2.5-3 percentage points can be removed at air temperature 50-60 °C. The retention time of the rough rice in these dryers should not exceed 20-30 minutes per pass. The exit kernel temperature should not be more than 35 °C. Due to the nonuniform distribution of moisture content within rice grains developed during the drying process, tempering time between passes in crossflow and mixed-flow dryers is usually selected to be 6-24 hrs (Brooker et al., 1992).

In a three-stage concurrent-flow (CCF) dryer, to maintain the quality of the rice, the maximum amount of moisture to be evaporated in one drying stage is 1.5-2.0% (w.b.). The time period in which rice is subjected to the hot air should be limited to 15-20 s, and the rice temperature in the tempering zones should not exceed 43 °C. The air temperatures are limited to 150-175 °C, 100-150 °C, and 75-125 °C, respectively, in the first, second, and third stages, and the grain velocity is maintained at 5-7 m/hr. The tempering time between drying stages at this grain velocity is approximately 1 hr, which is sufficient due to the uniformity of the average temperature and moisture content of the rice kernels entering the tempering zone (Brooker et al., 1992).

1.3 Drying models

The efficiency of drying systems can be improved by the analysis of the drying process. The analysis of drying process can be accomplished with the aid of a drying model. A drying model is normally used as a tool to explain the drying phenomena involved in the drying of grains in a mathematical from. The principle for developing a model is based on finding a set of mathematical equations which can adequately characterize the system of interest (Gunhun et al., 2005).

Drying is the process of removing moisture from the product or grain which involves simultaneous heat and mass transfer operations. The heat is used to evaporate moisture from the grain and a flow of air is employed to carry away the evaporated moisture. There are two basic mechanisms involved in the drying process: the migration of moisture from the interior grain kernel to the surface, and the evaporation of moisture from the surface to the surrounding air. The rate of drying illustrated in Figure 1.8 is determined by the moisture content and the temperature of the grain, the temperature, the relative humidity and the velocity of the air in contact with the grain.

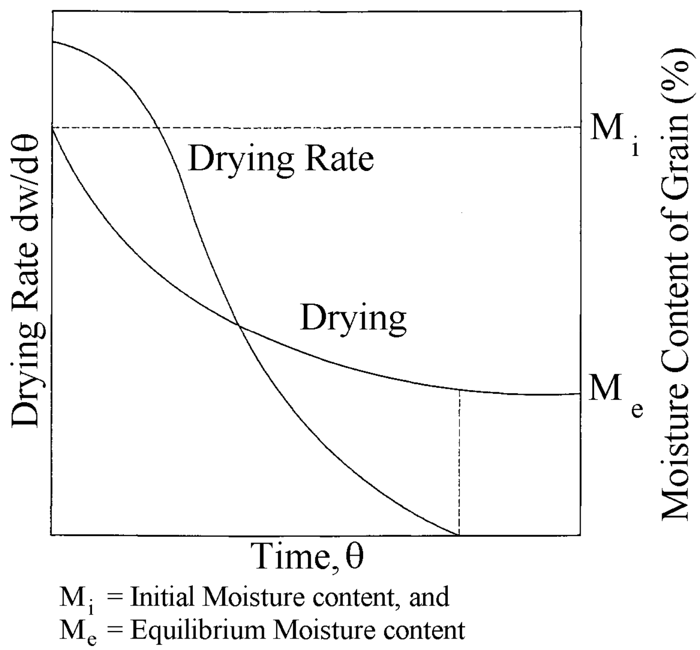


Figure 1.8. Drying rate (FAO, 1994).

Figure 1.8 shows the drying of a single layer of grain exposed to a constant flow of air. The moisture content falls rapidly at first and the rate of drying becomes slow while the grain loses moisture. In general, at high air temperature, moisture content, air flow rate and low relative humidity, the drying rate increases. On the contrary, at low air temperature, moisture content, air flow rate and high relative humidity, the drying rate decreases. However, the air velocity has a minimal effect on the drying rate because of the controlling mechanism of the moisture diffusion within the grain (FAO, 1994).

Many drying models were proposed as thin-layer drying equations developed form the thin-layer drying data. These equations form the basis for numerical analysis of deep-bed grain drying simulation (Agrawal and Singh, 1984; Noomhorm and Verma, 1986; Basunia and Abe, 1998). By definition, the term “thin-layer” is used to describe a layer of grain for which the temperature and relative humidity of drying air are homogeneous at any time and anywhere in a dryer (Cenkowski et al., 1993; Abud-Archila et al., 2000a).

Several works have been attempted to develop drying models to predict the drying rate but unfortunately, there is no single model which accurately predicts the drying rate for the entire range of drying operation found in practice. The rate of drying is affected by a number of factors such as initial moisture content, drying air temperature, relative humidity, depth and airflow rate. Other factors like type of grain, variety, drying method (e.g. intermittent drying), dryer type and efficiency of the dryer can also affect the rate of drying (Madamba and Yabes, 2005). An approach and a number of factors which take into account for consideration of their effects on a drying rate are diverse among the researchers. For example, the drying model proposed by Shei and Chen (1998) considered rice as one compartment; temperature and relative humidity of drying air, drying time and tempering time were the factors affecting the drying rate while the model proposed by Toyoda (1992) considered rice as a two-compartment entity; drying temperature and drying time were the factors affecting the drying rate.

The drying models can be broadly categorized into two groups: empirical models and theoretical models. A review of empirical and theoretical models proposed in a grain drying can be found in Jayas et al. (1991) and Brooker et al. (1992). Empirical models were developed by fitting experimental data with a simple mathematical function which mostly was in the form of exponential function (Agrawal and Singh, 1977; Wang and Singh, 1978; Sharma et al., 1982; Noomhorm and Verma, 1986; Basunia and Abe, 1998; Shei and Chen, 1998; Chen and Wu, 2000). Their advantage is that they are in a simple from of mathematical function which is easy to implement. However, they are valid only within the range of operating conditions which they were developed for. Theoretical models are developed based on the principles of heat and mass balances (Abud-Archila et al., 2000a; Rumsey and Rovedo, 2001; Wu et al., 2004). Their validity depends on the assumptions/simplifications employed. They have a common form, can be applied to a wide range of operating conditions but they are more difficult to implement.

1.4 Research Objective

The overall objective of this research is to thoroughly investigate the use of various types of drying models to the synthesis problem of rice drying process. In particular, the issues related to the application of a mathematical programming approach to solve different class of optimization problems arising from different types of process models applied to the problem are to be investigated. The solution of the synthesis problem sought is an optimal configuration and operating conditions of a rice drying system which meets the desired specification while optimizing a given optimization criteria.

1.5 Outline of the Research

The organization of the chapters of the thesis is as follows:

Chapter 1: Provides the background issues related to the drying process of rice and organization of the thesis.

Chapter 2: Presents the development for superstructure for the synthesis problem of rice drying processes, and addresses as well as review of the issues related to the application of mathematical programming approach to the synthesis problem dealing with different kinds of process models.

Chapter 3: Investigate the synthesis problem with various kinds of empirical drying models proposed in the literature as well as study the benefit of using generalized disjunctive programming as an alternative to MINLP.

Chapter 4: Investigate the synthesis problem with theoretical drying models proposed in the literature as well as propose a solution strategy to solve the resulting MIDO problem.

Chapter 5: Provides a summary of the overall findings of the research and recommendations for future work.

Chapter 2
Synthesis of Rice Drying Processes

2.1 Introduction

Various drying models have been developed and proposed in the extent which they are available for an analysis of drying processes for a variety of drying systems found in practice. Most of them were applied in the area of simulation and optimization focused only on a single unit operation (Barre et al., 1971; Noomhorm and Verma, 1986; Courtois et al., 2001; Shei and Chen, 2002; Zare et al., 2006). Many of them focused on the dryer; nevertheless other unit operations such as cooling and tempering units are also employed in industrial drying systems. Moreover, various drying configurations and operating conditions have been employed in rice drying processes. Phongpipatpong (2003 a,b,c) first addressed the integrated analysis of rice drying processes and stated that there are a large number of combinations of drying policies and operating conditions to dry rice to safe storage but the question of what is the best process structure or policy and operating conditions of rice drying plant that yield the best performance had not been answered yet. Therefore, there is an important need for application of the process synthesis in rice drying processes to provide the answer to this question. Process synthesis will take into account all the interactions between units that appear in a drying process simultaneously to select a particular system out of the large number of alternatives and operating conditions which meet the specified performance. This problem has been successfully applied in many chemical industries but not in the agricultural sector such as rice drying.

Process synthesis, or conceptual process design, is the act of determining the optimal interconnection of processing units as well as the optimal type and design of the units within a process system. The interconnection of process units is called the structure of the process system and therefore the task of the design engineer is to select a particular system out of the large number of alternatives and operating conditions which meet the specified performance (Nishida et al., 1981).

To solve the synthesis problem, mathematical programming becomes a major methodology in the area of process synthesis because of the advances in algorithms, modeling systems and software for solving various types of optimization problems. Furthermore, it provides a general systematic framework which can cope with a variety of different synthesis problems with the same mathematical tools (Yeomans and Grossmann, 1999). A review of the advances that have taken place in the mathematical programming approach to process design and synthesis is provided by Grossmann et al. (1999). This review presented the algorithms that are available for solving MINLP problems. The formulation of superstructures, models and solution strategies was also discussed for the effective solution of the corresponding optimization problems.

There are three major steps normally involved in the application of mathematical programming in a synthesis problem: first, the development of a superstructure to represent all alternatives from which the optimum solutions are selected; second, the formulation of a mathematical program which transforms the qualitative information from a superstructure into a quantitative one, third, the solution strategy for the optimization model from which the optimal solution is obtained (Yeomans and Grossmann, 1999).

Based on the above discussion, in this research we will extended the work of Phongpipatpong (2002) ,which studied the synthesis problem of rice drying processes using the simplified models, to thoroughly investigate the synthesis problem of rice drying processes with various kinds of drying models proposed in the literature. Both empirical (simplified) and theoretical (rigorous) models will be used for the analysis. The objective of this chapter is to address the issues related to the application of the mathematical programming approach to the synthesis problem dealing with different kinds of process models. The remainder of the chapter is structured as follows. First, the synthesis problem in rice drying processes will be addressed in Section 2.2. Then, the synthesis steps of mathematical programming methods will be presented. The development of superstructures is discussed in Section 2.3, the problem formulations in Section 2.4 and a review of solution strategies is given in Section 2.5. Finally the conclusions of this chapter are presented in Section 2.6.

2.2 Problem Statement

It is a matter of fact that rice needs to be dried to reduce moisture content from the harvested moisture content to a safe storage level ($\approx 14\%$ dry basis) and generally this process requires multi-sequences exposure of rice to drying, cooling and tempering units which are arranged differently depending on which drying system is used. Moreover, rice fissuring is a major problem in the rice industry and takes place due to improper drying. This leads to the breakage of rice grain in the milling process and therefore causes the loss of head rice yields (HRY). Head rice yield of rice is especially sensitive to the mode of drying and is normally used in assessing the success or failure of a rice drying system. Also the value of rice is directly determined by the yield of head rice. Thus, the economic importance of maintaining high HRY is critical during the drying process (Spadaro et al., 1980).

Another issue of major concern in rice drying is energy consumption. Energy conservation and efficient energy use are increasingly important today in various agricultural operations due to the fluctuation of energy cost in the global market. Rice, like many other grain crops, requires a very intensive amount of energy to heat up the supply air in artificial drying. Actual energy requirements for evaporating water from grain range from 3 to 8 MJ/kg of water (Brooker et al., 1992). Factors such as type and variety of grain, moisture content, physical properties of grain, drying air temperature and flow rate, and type of drying method used all affect the drying rate and energy use (Gunasekaran, 1986). Many researchers have been trying to design the rice drying system which meets the requirement for high grain quality and less energy consumption (Prachayawarakorn et al., 2005; Atthajariyakul and Leephakpreeda, 2006).

Therefore, the arising question in rice drying processes is: "*how can we find the best configuration for a drying system and what are its proper operating conditions to meet the desired specifications while optimizing a given objective or goal function?*" In other word, the synthesis problem in this research can be addressed as follows: "*Given a specified initial moisture content and final moisture content, what is the best configuration of flowsheet and its optimum operating conditions which optimize a given optimization criteria and meet the desired specifications?*".

To be able to answer these questions, process synthesis using mathematical programming, known as a tool for determining the optimal interconnection of processing units as well as the operating conditions under a given decision criteria, will be considered in this research. Phongpipatpong (2002) stated that rice processing has many features that lead to difficulty in applying traditional process analysis, design, simulation and optimization techniques. She first applied the systematic tools that can address the drying problems encountered. The mathematical programming method was used for the synthesis problem of rice drying using simplified models which lead to MINLP problem. The synthesis problem was solved under six different criteria: production time, number of the operating units, energy consumption, total operating cost, head rice yield and profit to find the best flowsheet structure and optimum operating conditions for drying processes.

Maximizing the yield of head rice and/or minimizing the energy consumption have been considered as the optimization goal in many rice drying studies (Gunasekaran, 1986; Brooker et al., 1992; Franca et al., 1994; Phongpipatpong, 2002; Atthajariyakul and Leephakpreeda, 2006; Thakur and Gupta, 2006b). Therefore, throughout this research, these two objective functions will be considered as our optimization goals for the synthesis problems.

2.3 Development of Superstructure

A superstructure is a graphical representation which includes all possible design alternatives of process equipments as well as their connectivity, from which the optimal design will be selected (Grossmann et al., 1999). Developing an appropriate superstructure is clearly important, as the optimal solution obtained can only be as good as the representation that is being used. The set of information required to postulate the superstructure is equipment, raw materials, products, process alternatives and interconnections among them (Yeomans and Grossmann, 1999). Traditionally a superstructure is developed in an ad hoc basis for a specific problem type. Yeomans and Grossmann (1999) developed a systematic framework for the development of superstructures. They used the state task network (STN) and state equipment network (SEN) as two fundamental representations of superstructures for process systems involving mass, heat and momentum transfer. A discussion of works and ideas which have emerged for constructing a superstructure representation can be found in Grossmann et al. (1999). In the following section, information needed to construct the superstructure for our synthesis problem will be addressed.

2.3.1 Raw material and product

This work focuses on the synthesis process of rice drying processes; therefore the raw material is rice grain at high level of moisture content (e.g. its harvested moisture content) and the product is rice grain at the desired level of moisture content for safe storage (e.g. 14% dry basis).

2.3.2 Equipment

There are various types of drying systems that are used nowadays depending on many factors such as investment cost, term of use and available technology. Nevertheless, the most popular one is the multi-pass drying system and is therefore the focus of this work. The reason is that drying rice is to prevent deterioration due to excess moisture content for a safe storage level of rice grain; however, this operation affects the quality of dried rice on which market value is placed. This is so because physical characteristic of the rice grain (which is composed of hull and brown rice layer) has a different potential in losing the moisture content. Thus, there is a development of a moisture gradient if rice is dried too fast in one pass (Brooker et al., 1992). The multi-pass drying system consists of multi-sequence exposure of rice drying, cooling and tempering units which are arranged in different sequences. Therefore, the set of equipment employed to construct the superstructure in this research is drying, cooling and tempering units.

2.3.3 Process alternatives and interconnections among them

From all the elements described above, two superstructures which represent the alternatives and interconnections among the unit operations are proposed. One is for the synthesis problem of rice drying processes using empirical models and another one is for the synthesis problem using mechanistic (theoretical) models. The first superstructure used for the empirical models consists of 3 alternatives: drying- tempering, cooling-tempering and drying-cooling-tempering in each pass as shown in Figure2.1. In Figure 2.1, rice at initial moisture content (M_i) will pass through multi-pass sequences (j) of drying (D_j), cooling (C_j) and tempering (P_j) units till the moisture content of rice gain reaches the safe storage level (M_f). Nodes $S1_j$ to $S4_j$ and nodes $M1_j$ to $M4_j$ are the dummy splitting and mixing nodes which do not actually exist in a real drying system. They are used for the flowsheet representation only and to facilitate the connectivity of unit operations in the superstructure easily.

These 3 alternatives were first considered in the work of Phongpipatpong and Douglas (2003b) for the synthesis problem of rice drying processes with their own developed empirical models. They will be used again in this work for the study of the rice drying synthesis problem using various empirical models.

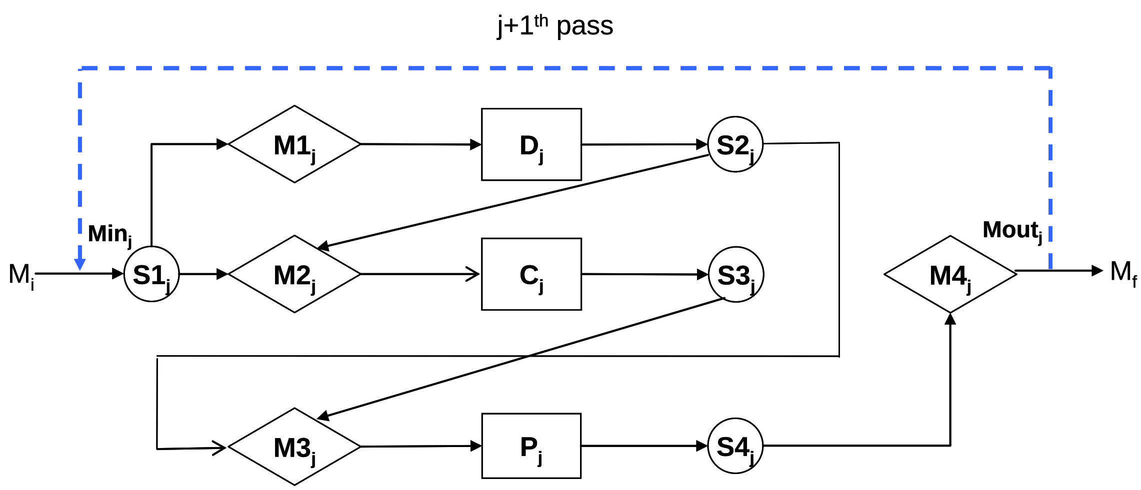


Figure 2.1. Three-alternative superstructure representation of synthesis of rice drying processes using empirical models.

The second superstructure is the extension of the first superstructure which includes another two alternatives, drying-cooling and drying-tempering-cooling as shown in Figure 2.2. This extended superstructure will represent all possible configurations of practical rice intermittent drying systems. For example, the most popular commercial dryer (cross-flow) which includes both drying and cooling within one dryer, will be represented with the sequence of drying-cooling. The two-stage concurrent flow dryer is represented with the sequences of drying-tempering for the first stage and drying-cooling for the second stage (Hawk et al., 1978).

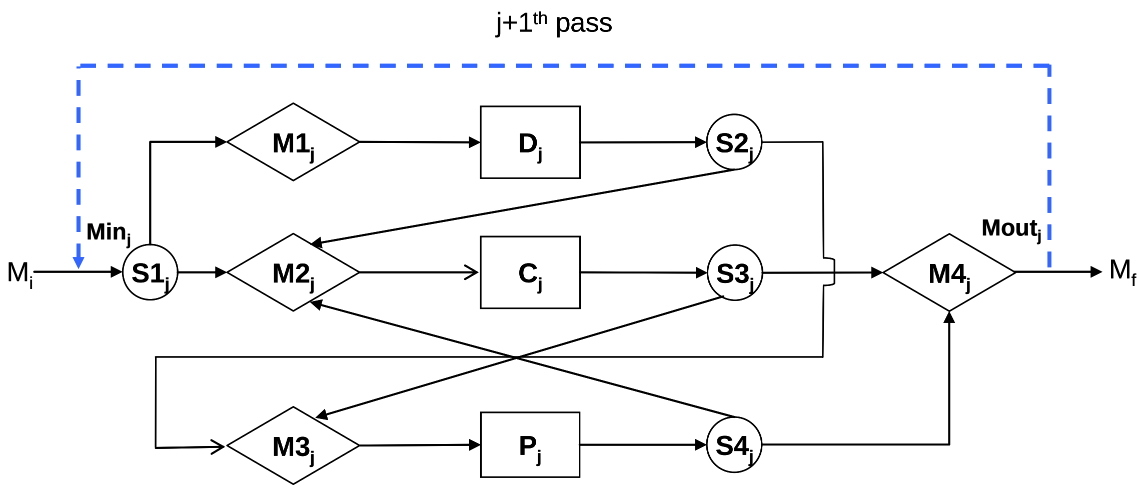


Figure 2.2. Five-alternative superstructure representation of synthesis of rice drying processes using theoretical models.

Moreover, our second superstructure can represent the choices of fluidized-bed drying systems which were investigated experimentally and by simulation by Prachayawarakorn et al. (2005). The objective of their study was to find the fluidized-bed drying system which can reduce the moisture content of paddy down to 16.5 % dry basis while maintaining the yield of head rice. Also maintaining the grain color and energy consumption were another factors which were taken into account. Three drying systems which were considered are: drying-tempering-cooling (system No.1), drying-tempering-cooling in the first pass and drying-tempering-cooling in the second pass (system No.2), and drying-tempering in the first pass and drying-tempering-cooling in the second pass (system No.3).

Note that in system No.2, a tempering unit is added between the passes but later on in their work they found that adding this unit did not significantly affect the yield of rice. Their results showed that system No.2 provided the best quality of rice grains among the others.

The reasons that only three alternative superstructures were used for the synthesis problem with empirical models because similar work done by Phongpipatpong and Douglas (2003b) recommended that using 3 alternatives with a maximum total number of passes equals to 8 will generate 6,561 possible configurations which represents a reasonable size of discrete variables to solve with available optimization software. Another reason is that the developed empirical model of head rice yield (HRY) employed here did not consider the effect of tempering condition as a cause of reduction in head rice yield(required time calculated from the tempering model into account). In other words, the developed empirical models considered the drying conditions (operating variables) employed in drying and/or cooling units as the only reason which causes the reduction of head rice yield. The effect of moisture gradient that normally causes the reduction of head rice yield was opted out from the empirical models based on the assumption of the tempering model. The assumption applied to the tempering model is that the model will find the tempering time needed to completely equilibrate the moisture gradient developed within a rice grain due to drying process (Phongpipatpong and Douglas, 2003a).

Therefore, using the empirical models in the synthesis problem is not able to provide the information of the importance of having a tempering unit in a rice drying system. As a result, the synthesis problem with empirical models cannot explain the different effects between having a configuration of drying-cooling-tempering and drying-tempering-cooling in a drying system on head rice yield. Note that these models are suited for the superstructure developed by Phongpipatpong and Douglas (2003b) because one condition applied to their superstructure is that if once a drying or cooling unit exists in a rice drying system, there must be a tempering unit. Nevertheless, using theoretical models in the synthesis problem of rice drying processes can eliminate this limitation.

The theoretical models (Abud-Archila et al., 2000a) employed to unit operations in this work are based on the same basis of heat and mass balances which consider how the air properties (drying conditions) affect the state of moisture content in rice grain and how this state of moisture content results in a reduction of HRY (the details of models will be provided in Chapter 4). For this reason, using theoretical models with the synthesis problem will provide the sources of information needed to investigate the effect of all possible configurations proposed in the second superstructure on the quality of rice grain.

2.4 Problem Formulation

At this step, problem formulation, information contained in a superstructure will be transformed into a mathematical form. The synthesis problem involves the selection of a configuration or topology, as well as its design parameters. On one hand, which process units should be integrated into a flowsheet and how they should be interconnected must be determined while on the other hand, the sizes and operating conditions of the units must be decided. The first decision involves clearly making a choice in a discrete space while the latter involves making choices in a continuous space.

Therefore, design and synthesis problems normally give rise to discrete/continuous optimization problems, which when represented in algebraic form, correspond to mixed-integer optimization problems that have the following form (Grossmann et al., 1999):

$$Min \quad f(x,y) \tag{2.1}$$

$$\text{s.t.} \quad h(x,y) = 0 \tag{2.2}$$

$$g(x,y) \leq 0 \tag{2.3}$$

$$x \in X, y \in \{0,1\} \tag{2.4}$$

where $f(x,y)$ is the objective function (e.g. cost). $h(x,y)=0$ are the process (e.g. mass and heat balances). $g(x,y) \leq 0$ are inequalities that define the specifications as well as constraints for feasible choices. x is a vector of continuous variables and generally correspond to the state or design variables. y is a vector of discrete variables, which are restricted to take 0-1 values to define the selection of an item or an action. Equation (2.1) to (2.4) corresponds to mixed-integer nonlinear program (MINLP) when any of the functions involved are nonlinear. If all functions are linear, it corresponds to a mixed-integer linear program (MILP). If there are no 0-1 variables, the problem reduces to a nonlinear program (NLP) or linear program (LP) depending on whether or not the functions are linear or non-linear.

Different process models employed in a synthesis problem will give rise to different types of the optimization problems. Banga et al. (2003) stated that a process model is an essential component of process system engineering methods and they are usually classified into three categories:

- First-principles (or white-box) models, which are derived from well known physical and chemical relationships, reflecting the underlying principles that govern the process behaviour.

- Data-driven (or black-box) models, which are of empirical nature.

- Hybrid (gray-box) models, which is a combination of the above two types of models.

In our work, the first two classes of models are represented in the synthesis problems of rice drying processes. The synthesis problem with the first principle model or theoretical model will give rise to the problem called mixed-integer dynamic optimization problem (MIDO) while the synthesis problem with the data-driven model or empirical model will give rise to the general class of synthesis problem, mixed-integer nonlinear programming (MINLP). Nevertheless, due to the issue that different mathematical models are often possible for the same synthesis problem and each of them has a different impact on the performance of the solution algorithm (Grossmann, 1990), the synthesis problem with empirical models will be first posed as a generalized disjunctive programming (GDP) model. The reason is that this modeling framework was proposed as a superior alternative to MINLP problems by Raman and Grossmann (1994). It has been accepted that it is more natural to start posing the synthesis problem with a GDP model (Grossmann and Lee, 2003) and it has favourable properties which can improve the performance of solution algorithms (Grossmann, 2002; Oldenburg et al., 2003).

2.4.1 Problem formulation for the synthesis problem with empirical models

As we mentioned before, the synthesis problem using empirical models will be posed as a GDP model. The basic idea of a GDP model is to express the problem in terms of general constraints which always hold (e.g. process models), disjunctions that correspond to discrete decision in the continuous space (e.g. a change of the stage variables in a multi-stage process), and logic propositions which involve only Boolean variables in the discrete space (e.g. connectivity of unit operations). These components of a GDP model make it very attractive for the formulation of the synthesis problem since the problem naturally lead to a model where the solution space is disjoint, and there is a strong logic on the connectivity among the different tasks (Raman and Grossmann, 1993; Raman and Grossmann, 1994). The general forms of a GDP model is shown below (Raman and Grossmann, 1994).

$$Min \;\; Z = \sum_{k \in K} c_k + f'(x) \tag{2.5}$$

s.t.

$$g'(x) \le 0 \tag{2.6}$$

$$\bigvee_{i \in I_k} \begin{bmatrix} Y_{ik} \\ h_{ik}{}'(x) \le 0 \\ c_k = \gamma_{ik} \end{bmatrix} k \in K \tag{2.7}$$

$$\Omega(Y) = \text{True} \tag{2.8}$$

$$x \in X, Y_{ik} \in \{\text{True, False}\} \tag{2.9}$$

where x is a vector of continuous variables and Y is a vector of the Boolean variables. The objective function involves the term $f'(x)$ for the continuous variables and the charges c_k that depend on the discrete choices. The equalities/inequalities $g'(x) \le 0$ must hold regardless of the discrete conditions, and $h_{ik}{}'(x) \le 0$ are conditional equations that must be satisfied when the corresponding Boolean variables Y_{ik} is true for the i^{th} term of the k^{th} disjunction. The set I_k represents the number of choices for each disjunction defined in the set K. Also, the fixed charge c_k is assigned the value γ_{ik} for that same variable. Finally, the constraints $\Omega(Y)$ involve logic propositions in terms of Boolean variables. In Chapter 3, the detailed formulation of the synthesis problem with empirical models as the GDP model will be provided.

However, due to progressively development of algorithms and codes for MINLP problems, most GDP models have been transformed into MINLP. Any problem posed as a GDP model can always be reformulated as an MINLP model, and vice versa (Grossmann, 2002). To transform a GDP model into MINLP, both the disjunctive and the proposition parts must be transformed.

For the proposition part, the relationship between logical relation and linear equality/inequality constraints represented in the work of Raman and Grossmann (1991) is normally employed. The detailed of this procedure will be shown in Chapter 3.

For the disjunctive part, there are two common methods have been proposed to transform a GDP model: Big-M constraint and convex hull formulation.

<u>Big-M constraints</u>:

For the GDP problem as shown in Equations (2.5) to (2.9), the MINLP model can be derived by replacing the Boolean variables Y_{ik} by binary variables y_{ik} and using Big-M constraints and logic constraints $\Omega(Y)$ with linear inequalities (Raman and Grossmann, 1991). The following MINLP is obtained (Lee and Grossmann, 2000);

$$MinZ = \sum_{k \in K} \sum_{i \in I_k} \gamma_{ik} y_{ik} + f'(x) \tag{2.10}$$

$$\text{s.t. } g'(x) \le 0 \tag{2.11}$$

$$h_{ik}'(x) \le M_{ik}(1 - y_{ik}), \quad i \in I_k, \quad k \in K \tag{2.12}$$

$$\sum_{i \in I_k} y_{ik} = 1, \quad k \in K \tag{2.13}$$

$$Ay \le a \tag{2.14}$$

$$x \ge 0, \quad y_{ik} \in \{0,1\}, \quad i \in I_k, \quad k \in K \tag{2.15}$$

In this model, M_{ik} is the big-M parameter which render inequalities $h_{ik}'(x)$ when $y_{ik} = 1$ and become redundant when $y_{ik} = 0$.

Convex-hull formulation:

By replacing x with the sum of disaggregated variables v^{ik}, and c with a combination of γ_{ik} with weight λ_{ik}, the following MINLP is obtained (Lee and Grossmann, 2001);

$$Min\ \ Z = \sum_{k \in K} \sum_{i \in I_k} \gamma_{ik} \lambda_{ik} + f'(x) \tag{2.16}$$

$$\text{s.t. } g'(x) \le 0 \tag{2.17}$$

$$x = \sum_{i \in I_k} v^{ik}, \quad \sum_{i \in I_k} \lambda_{ik} = 1, \quad k \in K \tag{2.18}$$

$$0 \le v^{ik} \le \lambda_{ik} U_{ik}, \quad i \in I_k, \quad k \in K \tag{2.19}$$

$$\lambda_{ik} h_{ik}{}' (v^{ik} / \lambda_{ik}) \le 0, \quad i \in I_k, \quad k \in K \tag{2.20}$$

$$Ay \le a \tag{2.21}$$

$$0 \le x, \quad v^{ik} \le U, \quad 0 \le \lambda_{ik} \le 1, \quad i \in I_k, \quad k \in K, \tag{2.22}$$

These two approaches have their own computational advantage and disadvantage. There is always a trade-off between these two techniques. Big-M constraints generate poor relaxations but small problem sizes while convex-hull formulation provide tighter relaxations but large problem sizes(Raman and Grossmann, 1994; Vecchietti et al., 2003; Sawaya and Grossmann, 2005). Tighter relaxations leads to a reduction in the search space while small problem sizes lead to a decrease in the solution time required per iteration and the total number of iterations per node (Sawaya and Grossmann, 2005).

The work from Vecchietti et al. (2003) provided the guidelines on which technique is worth to reformulate the disjunction by analyzing the feasible region of the relaxed MINLP model obtained from using either technique. They also proposed a technique called cutting plane method which can take advantage of tightening the relaxation bounds produced by convex hull and small problem size generated by BIG-M constraint for a GDP problem. However, there is a cost associate from building a cutting plane (solving QP separation problem) and this technique is limited to a linear GDP problem (Sawaya and Grossmann, 2005).

2.4.2 Problem formulation for the synthesis problem with theoretical models

Drying process can be theoretically described by the coupled heat and mass transfer and this is mathematically represented by a set of differential algebraic equations (DAEs). Differential equation arise from the description of transient mass and heat balances while algebraic equations emerge from the description of physical properties related to the process. Therefore, the problem formulation of the synthesis problem with the theoretical models gives rise to a class of optimization problems called mixed-integer dynamic optimization (MIDO). The general form of a MIDO model is shown below (Allgor and Barton, 1999).

$$\min_{u(t),v,y,t_f} \left\{ \phi(x(t_f),u(t_f),v,y,t_f) + \int_{t_0}^{t_f} L(x(t),u(t),v,y,t)dt \right\} \tag{2.23}$$

Subject to:

$$h(x(t),\dot{x}(t),u(t),v,y,t) = 0 \quad \forall t \in \lfloor t_0, t_f \rfloor \tag{2.24}$$

$$g(x(t),\dot{x}(t),u(t),v,y,t) \leq 0 \quad \forall t \in \lfloor t_0, t_f \rfloor \tag{2.25}$$

$$k_p(x(t_p),\dot{x}(t_p),u(t_p),v,y,t_p) \leq 0 \quad \forall p \in \{o, n_p\} \tag{2.26}$$

$$x \in X \subseteq R^{n_x}; u \in U \subseteq R^{n_u}; v \in V \subseteq R^{n_v} \tag{2.27}$$

where ϕ is the objective function at the final time, L is the objective function represented in an integral form $x(t)$ are the continuous variables describing the state of the dynamic system, $u(t)$ are continuous control variables whose optimal time profiles on the interval $[t_0, t_f]$ are required, v is continuous time invariant parameters, y a set of time invariant parameter that can only take discrete values, and t_f is a final time. Equation (2.24) represents a general set of differential–algebraic equations describing the dynamic system. Equation (2.25) represents general path equality/inequality constraints that must be satisfied by a solution of the optimization over the entire time period of interest. Finally, Equation (2.26) represents general point equality/inequality constraints.

2.5 Optimization Strategy

A different kind of drying model applied to the synthesis problem gives rise to a different class of optimization problems with various degrees of difficulty though they all aim to find the optimal configuration and operating conditions of rice drying process. This requires also different optimization techniques needed to solve the problems. Numerous optimization methods have been proposed and developed extensively but there is no generic method which can solve efficiently any type of optimization problem. Finding the proper choice of optimization methods to solve a problem at hand is a key issue for the successful application of the algorithms. In this section, an overview of relevant optimization methods which were proposed for each class of optimization problems arising from using different kinds of process models to the synthesis problem will be provided.

2.5.1 Solution strategy for generalized disjunctive programming models

There are few optimization algorithms and codes that have been proposed to solve the optimization problem in an original GDP model. Raman and Grossmann (1993, 1994) proposed a special branch and bound method which directly applies branching rules on logical inference. The interrelation between nodes in a flowsheet can be used to a priori fix some binary variables. They found that this method greatly reduced the number of search trees in the branch and bound method. LOGIMP is the first computer code for solving GDP, MINLP and hybrid GDP/MINLP models under GAMS environment. An example of the code to solve discrete/continuous optimization problems can be found in Vecchietti and Grossmann (2000).

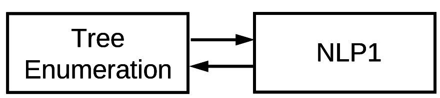
As mentioned in Section 2.4.1 most problems posed as GDP models can be transformed into MINLP models and solved with available MINLP algorithms. For example, Lee and Grossmann (2003) proposed the global optimization method based on branch and bound framework to solve process network problem which were formulated as GDP models. Convex hull formulation was used to transform their GDP model into an MINLP problem.

Major algorithms to solve an MINLP problem are branch and bound (B&B), Outer-Approximation (OA), and Generalized Benders Decomposition (GBD) (Grossmann, 1990; Grossmann et al., 1999).

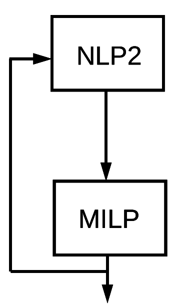
Basic elements of these three methods as described by Grossmann (2002) are NLP subproblems and MILP master problem (MILP). Also, there are three sub-classes of NLP subproblems as follows:

- NLP relaxation (NLP1)
- NLP subproblem for a fixed discrete variable (NLP2)
- Feasibility NLP subproblem for a fixed discrete variable (NLPF)

Different methods can be classified according to their use of those elements as shown in Figure 2.3. The basic idea of B&B is that it performs tree enumeration by solving NLP1 in both breadth and depth direction. The solution of NLP1 provides lower bound to MINLP. The node of tree will be fathomed when the lower bound exceeds the current upper bound, when the subproblem is infeasible or when all relaxed discrete variables take on integer values. The latter yields the upper bound to the problem. The optimal solution is found when all binary variables take integer values and NLP1 are solved to optimality at all nodes. The B&B method is generally attractive if NLP1 are relatively inexpensive to solve (Grossmann, 2002).



(a) B&B



(b) GBD, OA

Figure 2.3. Major steps of MINLP algorithms.

OA and GBD are similar in nature. At each major iteration, NLP2 will search for continuous variables and provides an upper bound to MINLP. If NLP2 is infeasible, problem NLPF will be solved instead to find infinity-norm to the problem. MILP will search for discrete variables and provides lower bound to the problem. The predict lower bound will increase monotonically as the cycle of major iterations proceeds and the search will be terminated when predicted lower bound equal or exceeds the current upper bound. The main difference between these two methods is the definition of the MILP problem. MILP of GBD is given by dual representation of continuous space while MILP of OA is given by primal linear approximation of continuous space (Grossmann, 2002).

In each iteration, GBD accumulates one Lagrangian cut in the space of discrete variables while OA accumulates a set of linear approximations of nonlinear constraints in both discrete and continuous space. Therefore, OA method predicts stronger lower bounds and requires fewer major iterations than the GBD method. However, computational demands on the MILP problem of OA are greater than GBD method (Grossmann, 1990).

2.5.2 Solution strategies for mixed-integer dynamic optimization models

In contrast to dynamic optimization problems (DO), only limited progress has been achieved in addressing mixed-integer dynamic optimization problems (MIDO) (Allgor and Barton, 1999; Chachuat et al., 2005). Currently reported technique to solve MIDO problems have relied on the extensions of decomposition approaches for solving MINLP problems (Barton et al., 1998; Allgor and Barton, 1999; Bansal et al., 2003; Oldenburg et al., 2003; Barton and Lee, 2004; Chachuat et al., 2005). Nevertheless, Balsa-Canto et al. (2005) investigated different hybrid stochastic-deterministic methods to find the efficient one to solve both single and multi stage optimization problems. The hybrid method was presented as a robust alternative for the solution of challenging nonconvex NLPs. The main idea of their hybrid strategy is the combination of a global stochastic method with a local deterministic method in order to take advantage of their complementary strengths: global convergence properties of the stochastic method, and fast convergence if started close to the global solution of the deterministic method.

Deterministic methods make use of analytical and systematic techniques as well as assumption on problem structures to find the optimum solutions, and often guarantee finite convergences within a prespecified level of accuracy (Banga et al., 2003; Balsa-Canto et al., 2005). Stochastic methods make use of pseudo-random numbers and do not require any assumption about the problem structure but the drawback is that optimality cannot be guaranteed. They can be a great alternative when deterministic methods cannot be applied, or require too much implementation work. Also the benefit that any assumption on problem structure is not required, thus they can handle any class of optimization problems (Banga et al., 2003).

For the solution strategies of dynamic optimization problems (DO), Bansal et al.(2003) stated that a number of algorithms have been developed in the literature for solving DO and their reliability has evolved to the extent that realistic engineering problems involving thousands of variables can now be readily solved with commercial codes such as gPROMS/gOPT. The numerical methods for the solution of DO are usually classified under three categories: dynamic programming, indirect and direct methods (Barton et al., 1998; Arpornwichanop et al., 2005; Banga et al., 2005).

Dynamic programming applies the principle of optimality to formulate an optimization problem, leading to the development of Hamilton-Jacobi-Bellman partial equations that determine the solution of DO problem. However, this approach is quite limited to a small problem due to the difficulty in obtaining the solution of the optimality equations (Arpornwichanop et al., 2005).

The indirect method is based on finding the numerical solution to the classical necessary conditions rather than solving the optimization directly. However, these methods can exhibit numerical instabilities or slow convergence rates for many problems (Zhahedi et al., 2007).

Finally, the direct method is based on the discretization techniques which received major attention and considered as an efficient solution method. The concept of this approach is to transform the original DO problem into a finite dimensional optimization problem, typically a nonlinear programming (NLP) problem. This approach can be divided into two categories: sequential and simultaneous strategies (Arpornwichanop et al., 2005).

In the sequential strategy, a control (optimization parameter) variable profile is discretized over a time interval. The discretized control profile can be represented as a piecewise constant, a piecewise linear, or a piecewise polynomial function. The parameters in such functions and the length of time subinterval become decision variables in the optimization problem. This strategy is also referred to as a control vector parameterization (CVP). One advantage of this approach is the small scale NLP that makes it attractive to apply for solving the optimal control with large dimensional systems that are modeled by a large number of differential equations. In addition, this approach can take the advantage of available initial value problem (IVP) solvers. However, the limitation of the sequential method is a difficulty to handle a constraint on state variables (path constraint). This is because the state variables are not directly included in NLP.

In the simultaneous approach, both state and control variables are discretized and this leads the simultaneous approach to a large scale optimization problem consisting of a large set of algebraic constraints and decision variables and needs a special solution strategy. In contrast to the sequential solution method, the simultaneous strategy solves the dynamic process model and the optimization problem at one step. This avoids solving the model equations at each iteration in the optimization algorithm as in the sequential approach. In this approach, the dynamic process model constraints in the optimal control problem are transformed into a set of algebraic equations which is treated as equality constraints in the NLP problem. The main advantage of the simultaneous approach is a capability in handing constraints on the state variables. A review of solution methods for solving DO problems can be found in Cervantes and Biegler (2000).

2.6 Conclusions

The overall picture of the synthesis steps applied in rice drying processes dealing with different types of process models was addressed. Three alternative superstructures were proposed for the synthesis problem dealing with the empirical models. Five alternative superstructures were proposed for the synthesis problem dealing with the theoretical models. Problem formulations arising from using different types of process models were addressed. A review of the literature related to solution strategies corresponding to different class of optimization problem was provided.

Chapter 3

Generalized Disjunctive Programming for Synthesis of Rice Drying Processes

3.1 Introduction

The synthesis problem of rice drying processes involves both discrete and continuous variables. Discrete variables are employed for discrete decisions of the connectivity among unit operations while continuous variables for decision of operating levels of unit operations involved in drying processes. Nevertheless, developing optimization models with discrete and continuous variables is not a trivial task. Different mathematical models are often possible for a same synthesis problem and each of them can have a very different performance with respect to the efficiency for solving the synthesis problems (Raman and Grossmann, 1994; Vecchietti et al., 2003).

For a decade, the relation of discrete and continuous variables in synthesis problem is normally developed in an ad hoc basis (intuitively by modellers) until Raman and Grossmann (1994) proposed a logic-based modeling framework for discrete/continuous problems called generalized disjunctive programming (GDP) as an alternative model to MINLP. Grossmann and Lee (2003) stated that it is more systematic and natural to start posing a synthesis problem as a GDP model because the model allows at the modeling stage the specification of mixture of algebraic and logic equations which are often found in the synthesis problem while the MINLP is based entirely on algebraic equations. As a result, GDP models have been widely applied in areas of discrete/continuous optimization problems such as design, synthesis and scheduling due to their ability to facilitate the modeling technique and enhance the solution efficiency (Raman and Grossmann, 1994; Turkay and Grossmann, 1996; Lee and Grossmann, 2000; Vecchietti and Grossmann, 2000; Oldenburg et al., 2003; Karuppiah and Grossmann, 2006). Therefore, the interest in this chapter is to apply the GDP framework to the synthesis problem of rice drying processes first studied by Phongpipatphong and Douglas (2003b) as a mixed-integer nonlinear program (MINLP).

The synthesis work of Phongpipatphong and Douglas (2003b) was performed by using their own developed empirical models (Phongpipatphong and Douglas, 2003a) for the analysis of their drying processes under various objective functions. However, apart from the simplicity in the development and employment of empirical model, these models are not without limitation. They can be used only within the range from which they were developed. As a result, various empirical-drying models have been proposed and available from the literature to be employed for the analysis of a wide range of drying operations found in practice (Agrawal and Singh, 1977; Wang and Singh, 1978; Sharma et al., 1982; Noomhorm and Verma, 1986; Basunia and Abe, 1998; Shei and Chen, 1998; Chen and Wu, 2000). Conventionally, researchers compared many drying equations and selected the one which best fits their thin-layer drying data (Wang and Singh, 1978; Noomhorm and Verma, 1986; Akpinar et al., 2003; Gunhan et al., 2005; Baini and Langrish, 2007). Note that empirical drying models were normally developed from thin-layer drying data. These thin-layer models are useful for simulation of drying processes where it is normally assume that a dryer consists of a series of thin layers placed one over the other.

In this chapter, the synthesis problem of rice drying processes will be investigated with various empirical drying models available in the literature which are valid in a different range of drying operations. Moreover, the synthesis problem which integrates a choice of drying models under the GDP framework will be studied to eliminate the problem of having various empirical models valid in a small range of drying operations. The remainder of this chapter is structured as follows. First, the synthesis problem in rice drying processes will be stated in Section 3.2. Then, the derivation of GDP model for the synthesis problem will be shown in Section 3.3. In Section 3.4, the application of GDP model to tackle the synthesis problem of drying processes using various proposed drying models is illustrated with three case studies and the results will be presented in Section 3.5. Finally, the conclusion of using GDP modeling in the synthesis problem will be drawn in Section 3.6.

3.2 Synthesis Problem of Rice Drying Processes

As described in Chapter 2, there is a need for an integrated analysis of rice drying processes (process synthesis) due to a large number of combinations of drying policies and operating conditions have been found in practice but the best drying system and operating conditions which yield the best performance have not been well explored yet (Phongpipatpong, 2002). Therefore, the objective of the synthesis problem in rice drying processes is to find the best process configuration and operating conditions of rice drying systems which yield the best performance under certain optimization criteria while satisfying the constraints.

The major problems in rice drying industries is that improper operation causes the fissuring problem which lower yield of head rice (quality) resulting in a lower market value of rice grain. Also, drying processes require an intensive use of energy. These two important drying problems will be considered as optimization goals of the synthesis problem. One aim is to find the optimum drying configuration and operating conditions which maximize the head rice yield while another one aims to minimize the energy consumption. The objective functions are shown in Equations (3.1) to (3.3). All functions were developed by Phongpipatpong and Douglas (2003a).

<u>Maximize head rice yield</u>:

$$HRY = 1 - 5.136353kt \tag{3.1}$$

where HRY is the yield of head rice (%decimal); k is a drying constant in drying or cooling models; and t is drying or cooling time (hrs).

<u>Minimize Energy Consumption:</u>

Energy function for a drying unit:

$$E_D = 2.50216 + 0.02349T_D \tag{3.2}$$

where E_D is energy consumption for a drying unit (MJ/kg water removed); T_D is drying temperature (°C).

Energy function for a cooling unit:

$$E_C = 8.45000 - 0.18167T_C \tag{3.3}$$

where E_C is energy consumption for a cooling unit (MJ/kg water removed); T_C is cooling temperature (°C).

In this work, mathematical programming will be used as a tool to solve the synthesis problem. This approach requires 3 steps to solve the synthesis problem; the representation of superstructure, problem formulation and optimization strategies.

The proposed superstructure for the synthesis problem with empirical models is shown in Figure 3.1. There are three alternative choices of drying configurations contained in the superstructure. The alternatives are drying-tempering, cooling-tempering and drying-cooling-tempering. The reasons that these three alternatives are considered for the synthesis problem with proposed empirical models were described in Chapter 2.

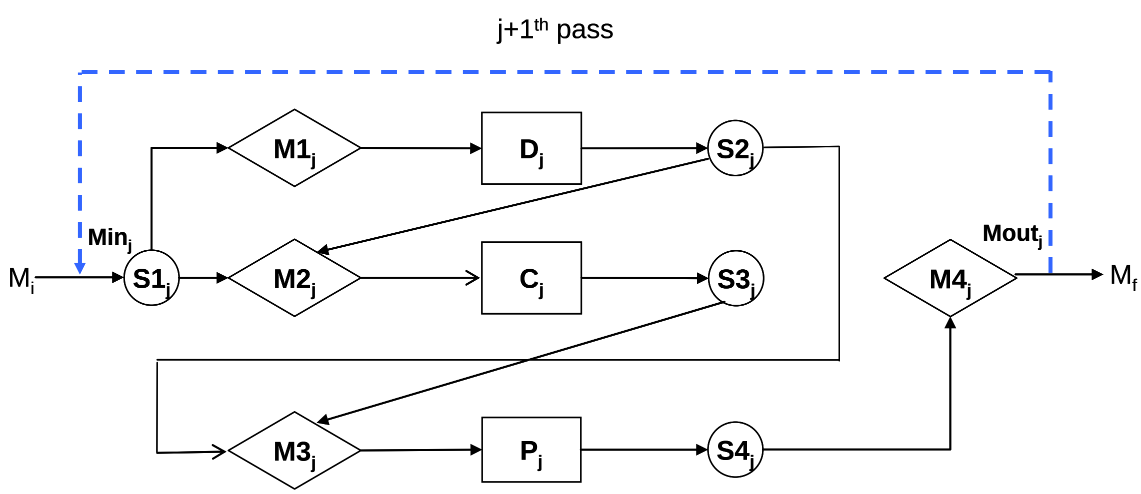


Figure 3.1. Three-alternative superstructure representation for the synthesis problem with empirical drying model.

From Figure 3.1, rice at initial moisture content (M_i) will pass through multi-pass sequences (j) of drying (D_j), cooling (C_j) and tempering (P_j) units till the moisture content of rice gain reaches the safe storage level (M_f). As mentioned in the previous chapter nodes $S1_j$ to $S4_j$ and nodes $M1_j$ to $M4_j$ are the dummy splitting and mixing nodes which do not actually exist in a real drying system. They are used for the flowsheet representation only and to facilitate the connectivity of unit operations in the superstructure easily.

In this work the general conditions applied for the synthesis problem are shown in Table 3.1. These conditions were also applied in the work of Phongpipatpong and Douglas (2003b). However, note that not all the drying conditions applied in Phongpipatpong and Douglas (2003b) are considered here because later on in this work the synthesis problem will be applied with more complicated descriptive empirical models and compared to the work of Phongpipatpong and Douglas (2003b). Therefore, to make sure that our synthesis problem can be solved with commercial optimization software (e.g. GAMS), only design criteria which are generally found in common practice of any rice drying system were selected as constraints in this work.

Table 3.1. General conditions considered for the synthesis problem with empirical models.

Condition	Description	Bound
1	Initial moisture content is 34% d.b.	$M_i = 34\%$ d.b.
2	Moisture removal per pass should less than 6% dry basis to prevent grain damage	$Min_j - Mout_j \leq 6\% d.b.$
3	Maximum number of passes is 8	$j \leq 8$
4	The desired final moisture content should be less than 14% d.b.	$M_f \leq 14\% \, d.b.$
5	Maximum head rice yield = 70%	$HRY_{\max} = 70\%$

In the following section the other steps (problem formulation and optimization strategies) required for the application of the mathematical programming approach to the synthesis problem will be described in details.

3.3 Generalized Disjunctive Programming Model

In the following section, the descriptive information contained in the superstructure will be transformed into the quantitative information as mathematical models using GDP approach for the synthesis problem. The general forms of GDP models for the synthesis problem are shown below.

The GDP formulation for the case of maximization of head rice yield is as follows:

$$Max \prod_{j=1}^{8} HRY_j \tag{3.4}$$

Subject to

$$g_j{}'(x_j) \le 0 \qquad ;\forall j \in J \tag{3.5}$$

$$\bigvee_{i \in I_k} \begin{bmatrix} Y_{ik_j} \\ h_{ik_j}{}'(x_j) \le 0 \end{bmatrix} \qquad ;\forall i \in I, \forall j \in J, \forall k \in K \tag{3.6}$$

$$\Omega(Y) = \text{True} \quad ;\forall i \in I, \forall j \in J, \forall k \in K \tag{3.7}$$

$$x \in X, Y_{ik_j} \in \{\text{True, False}\} \tag{3.8}$$

The problem formulation for the case of minimization of energy consumption is as follows:

$$Min \sum_{\text{j}=1}^{8} (E_{D_j} + E_{C_j}) \tag{3.9}$$

Subject to

$$g_j{}'(x_j) \le 0 \qquad ;\forall j \in J \tag{3.10}$$

$$\bigvee_{i \in I_k} \begin{bmatrix} Y_{ik_j} \\ h_{ik\,j}{}'(x_j) \le 0 \end{bmatrix} \qquad ;\forall i \in I, \forall j \in J, \forall k \in K \tag{3.11}$$

$$\Omega(Y) = \text{True} \quad ; \forall i \in I, \forall j \in J, \forall k \in K \tag{3.12}$$

$$x \in X, Y_{ik_j} \in \{\text{True, False}\} \tag{3.13}$$

where x_j is the vector of continuous variables in each pass $j \in J$, and Y_{ik_j} are Boolean variables. $g_j'(x_j)$ are common constraints that hold regardless of the discrete decisions. The disjunctions $k \in K$ are composed of a number of term $j \in J_k$ that are connected by the OR operator ($\vee$). In each term there are a number the Boolean variables Y_{ik_j} and a set of equality/inequality constraints $h_{ik_j}'(x_j)$. If Y_{ik_j} is true, then $h_{ik_j}'(x_j) \leq 0$ are enforced. Otherwise, the corresponding constraints are ignored. Also $\Omega(Y) = \text{True}$ are logic propositions for the Boolean variables.

For the problems posed above, there are several algorithms that have been proposed to directly solve the optimization problems in a GDP form or transform it into algebraic form (MINLP). An overview of proposed algorithms to solve the GDP model in both forms can be found in Vecchietti and Grossmann (2000). Nevertheless, due to the extensive development of algorithms and codes which are available for solving many practical MINLP problem, most GDP models are transformed and found to be solved in algebraic forms (Turkay and Grossmann, 1996; Lee and Grossmann, 2001; Lee and Grossmann, 2003; Sawaya and Grossmann, 2005; Karuppiah and Grossmann, 2006). Therefore, in this work a transformation of GDP models into algebraic models will be employed to be able to solve the synthesis problems in GAMS.

In the GDP models, there are two parts of the problem that need to be transformed: a disjunctive (Equations (3.6) and (3.11)) and proposition parts (Equations (3.7) and (3.12)). For the proposition parts, the procedure proposed by Raman and Grossmann (1991) will be employed. They proposed a procedure to systematically convert qualitative information (logic relations) contained in a flowsheet synthesis problem into integer constraints. The details of this procedure will be explained in Section 3.3.2.

For a disjunctive part, there are two common methods normally used to transform a GDP model into a MINLP model: convex hull formulation and Big-M constraints. A detailed discussion of these two techniques was provided in Chapter 2.

In this work, to avoid increasing the number of variables and constraints to the synthesis problem, Big-M constraint is selected as a technique to transform the disjunctive part of the GDP model into the algebraic form. The detailed formulation of this technique will be provided in Section 3.3.3. In the following section, each component of the GDP models will be addressed for the synthesis problem.

3.3.1 General constraints

General constraints which always hold regardless of the discrete decisions (as shown in Equation (3.5) and (3.10)) in the synthesis problem are process models. Process models are needed for describing the drying phenomena happening in the processing units involved in the superstructure which are drying, cooling and tempering units. As mentioned before, there is no single drying model which represents the drying process of rice grain over a wide range of drying operation. Here, the drying models developed from Wang and Singh (1978), Basunia and Abe (1998) and Phongpipatpong and Douglas (2003a) are selected as alternative choices of process model for the synthesis problem operating at various range of drying operation. The reason that their works were selected is that their drying models were developed as a function of the same operating variables (drying temperature, relative humidity of drying air and drying time). Moreover, all of them derived the models by fitting their drying data on a basis form of Page's model which has the general form as:

$$MR = \frac{M_t - M_e}{M_i - M_e} = \exp(-kt^N) \qquad (3.14)$$

where MR is moisture ratio; M_t is moisture content of grain at anytime (%d.b.), M_i is initial moisture content of grain (%d.b.), M_e is equilibrium moisture content of grain (%d.b.), t is drying time; k and N are drying parameters.

Wang and Singh's model:

Wang and Singh (1978) developed the equations for parameter k and N which are valid in the range of drying temperature between 30 and 55 ^{O}C and relative humidity of drying air between 15% and 85% as shown in Equation (3.15) and Equation (3.16).

$$k = 0.01579 + 0.0001746T - 0.01413RH \tag{3.15}$$

$$N = 0.6545 + 0.002425T + 0.07867RH \tag{3.16}$$

where T is air temperature (^{O}C), RH is relative humidity (%decimal).

Basunia and Abe's model:

Basunia and Abe (1998) proposed empirical equations for the parameters k and N for low range of drying temperature between 11.8 and 51^{O}C and relative humidity between 37.1% and 91.3% as shown in Equation (3.17) and Equation (3.18).

$$k = 0.0139402 + 0.0002044T - 0.0158462RH \tag{3.17}$$

$$N = 0.558983 + 0.001772T - 0.196982RH \tag{3.18}$$

Phongpipatpong and Douglas's model:

Phongpipatpong and Douglas (2003a) developed the process models for a drying, a cooling and a tempering unit with the purpose of having the models validated over a wide range of drying operation and simple enough for their use in the synthesis problem.

1. Drying model:

Page's model was simplified by setting $N = 1$ and $M_e = 0$; thus the drying model has the form as:

$$MR = \frac{M_t}{M_i} = \exp(-k_D t_D) \tag{3.19}$$

$$k_D = 0.023962T_D + 0.219931RH_D - 0.037472T_D RH_D \tag{3.20}$$

$$35 \le T_D \le 150 \tag{3.21}$$

$$0 \le RH_D \le 65 \tag{3.22}$$

where k_D is drying parameter (hr^{-1}), t_D is drying time (hr), T_D is drying air temperature (^{O}C), RH_D is relative humidity of drying air (%decimal).

2. Cooling model:

The same concept of the simplified drying model was applied to the cooling model; therefore the cooling model has the form as:

$$MR = \frac{M_t}{M_i} = \exp(-k_C t_C) \tag{3.23}$$

$$k_C = 0.004927T_C - 0.037351RH_C \tag{3.24}$$

$$15 \le T_C \le 30\ ^O C \tag{3.25}$$

$$40 \le RH_D \le 60\ \text{(\%decimal)} \tag{3.26}$$

where k_C is cooling parameter (hr^{-1}), t_C is cooling time (hr), T_C is cooling air temperature (^{O}C); RH_C is relative humidity of cooling air (%decimal).

3. Tempering time model:

This model is the only model used in this work for predicting the time required in a tempering unit to completely equalize the moisture gradient developed within rice grain. The model has a form as:

$$t_P = 10.91926 - 0.22236T_{D/C} - 0.00034t_{D/C}^2 + 0.001241T_{D/C}^2 + 0.096641t_{D/C}mPin \quad (3.27)$$

where $T_{D/C}$ is temperature in either a drying or a cooling unit before entering a tempering unit, $t_{D/C}$ is drying or cooling time in hours, $mPin$ is moisture content of rice entering a tempering unit (%d.b).

3.3.2 Development of logical constraints

In this section, the derivation of logical constraints for the proposition part of the GDP model (as shown in Equations 3.7 and 3.12) for the synthesis problem will be presented. These constraints involve only discrete or binary variables which are used to define the connectivity among the process units and existence of them. First, the logical relationship presenting the structural relationship in the superstructure will be developed and then it will be transformed to its equivalent Boolean expression. After that, Boolean expression will be converted to linear equality or inequality constraint.

3.3.2.1 Logical expression

The procedure proposed by Raman and Grossmann (1993) is employed to systematically integrate the logic in the process flowsheet as follows:

1. Associate Boolean variables with every node in the graph:

From the superstructure, every pass j we will assign binary variable $M1_j$, $M2_j$, $M3_j$ and $M4_j$ for dummy mixing nodes; $S1_j$, $S2_j$, $S3_j$ and $S4_j$ for dummy splitting nodes; $v1_j$, $v2_j$, $v3_j$, $v4_j$, $v5_j$, $v6_j$, for arcs; D_j, C_j and P_j for a drying, a cooling and a tempering unit respectively as shown in Figure 3.2. When a node or arc exists in the superstructure, the corresponding binary variable will have a logical value of true or 1 otherwise a logical value of false or 0.

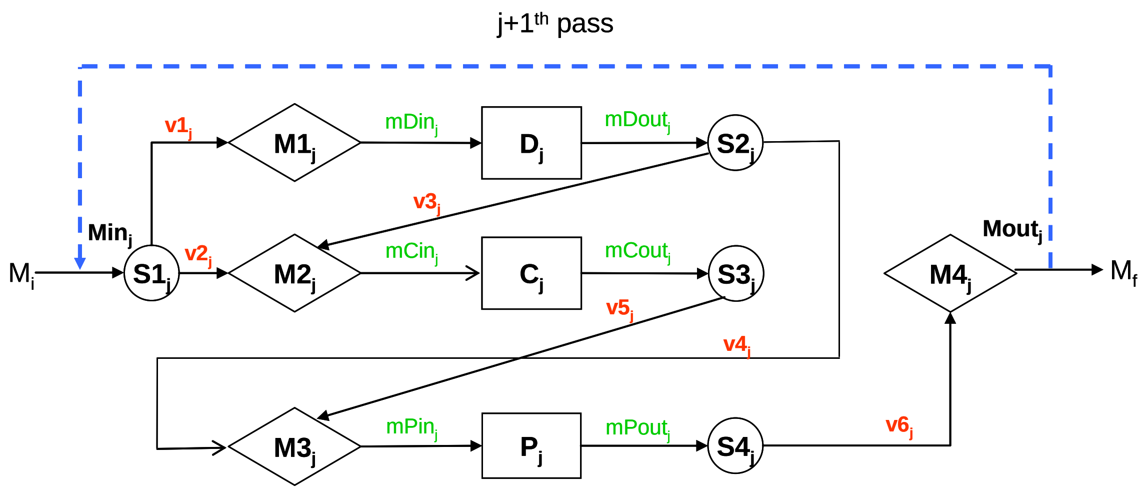


Figure 3.2. Three-alternative superstructure with the associated Boolean variables.

2. Develop relationships between Boolean variables:

Next, the logical relationship between Boolean variables in the superstructure will be expressed with logical operations; $\vee$ ("OR"), $\wedge$ ("AND), $\neg$ (negative, not), $\rightarrow$ ("implication") or $\leftrightarrow$ ("equivalent"). For example, the logical relations at every node in the superstructure are as follows:

<u>Node S1</u>: $S1_j \rightarrow M1_j \vee M2_j$ (3.28)

<u>Node M1</u>: $M1_j \rightarrow S1_j$ (3.29)

$M1_j \rightarrow D_j$ (3.30)

<u>Node M2</u>: $M2_j \rightarrow S1_j \vee S2_j$ (3.31)

$M2_j \rightarrow C_j$ (3.32)

<u>Node M3</u>: $M3_j \rightarrow S2_j \vee S3_j$ (3.33)

$M3_j \rightarrow P_j$ (3.34)

Node D: $D_j \rightarrow M1_j$ (3.35)

$D_j \rightarrow S2_j$ (3.36)

Node C: $C_j \rightarrow M2_j$ (3.37)

$C_j \rightarrow S3_j$ (3.38)

Node P: $P_j \rightarrow M3_j$ (3.39)

$P_j \rightarrow S4_j$ (3.40)

Node S2: $S2_j \rightarrow D_j$ (3.41)

$S2_j \rightarrow M2_j \vee M3_j$ (3.42)

Node S3: $S3_j \rightarrow C_j$ (3.43)

$S3_j \rightarrow M3_j$ (3.44)

Node S4: $S4_j \rightarrow P_j$ (3.45)

$S4_j \rightarrow M4_j$ (3.46)

Node M4: $M4_j \rightarrow S4_j$ (3.47)

3. Reduce the number of Boolean variables:

In the synthesis problem, our model does not require the assignment of 0-1 value to variables $M1_j$, $M2_j$, $M3_j$, $M4_j$, $S2_j$, $S3_j$ and $S4_j$. After apply the reduction procedure proposed by Raman and Grossmann (1993) to the equivalent logic relations represented in the superstructure, we found that:

$$M1_j \leftrightarrow D_j \leftrightarrow S2_j; \tag{3.48}$$

$$M2_j \leftrightarrow C_j \leftrightarrow S3_j; \tag{3.49}$$

$$M3_j \leftrightarrow P_j \leftrightarrow S4_j \leftrightarrow M4_j; \tag{3.50}$$

Therefore, the reduced logic after eliminating the unwanted variables is shown as follows:

$$S1_j \rightarrow D_j \vee C_j \tag{3.51}$$

$$D_j \rightarrow S1_j \vee C_j \vee P_j \tag{3.52}$$

$$C_j \rightarrow S1_j \vee D_j \vee P_j \tag{3.53}$$

$$P_j \rightarrow D_j \vee C_j \tag{3.54}$$

3.3.2.2 Boolean expression

From the above, the derivation of logical expressions for nodes in the superstructure was shown. Next, these logical expressions will be converted into its corresponding Boolean expressions. If we define each literal Y_i are a Boolean variable which has only two outcomes; true or false, the procedure of Clocksin and Mellish (1981) will be applied to transform a logical expression into its corresponding Boolean expression:

1. Replace the implication by its equivalent disjunction:

$$Y_1 \rightarrow Y_2 \Leftrightarrow \neg Y_1 \vee Y_2 \tag{3.55}$$

2. Move the negative inward by applying DeMorgan's Theorem:

$$\neg(Y_1 \wedge Y_2) \Leftrightarrow \neg Y_1 \vee \neg Y_2 \tag{3.56}$$

$$\neg(Y_1 \vee Y_2) \Leftrightarrow \neg Y_1 \wedge \neg Y_2 \tag{3.57}$$

3. Recursively distribute the "OR" over the "AND", by using the following equivalence:

$$(Y_1 \wedge Y_2) \vee Y_3 \Leftrightarrow (Y_1 \vee Y_3) \wedge (Y_2 \vee Y_3) \tag{3.58}$$

After applying the above procedure to Equations (3.51) to (3.54), the following Boolean expressions are obtained:

$$\neg S1_j \vee D_j \vee C_j \tag{3.59}$$

$$\neg D_j \vee S1_j \vee C_j \vee P_j \tag{3.60}$$

$$\neg C_j \vee S1_j \vee D_j \vee P_j \tag{3.61}$$

$$\neg P_j \vee D_j \vee C_j \tag{3.62}$$

3.3.2.3 Logical Constraints

The developed Boolean expressions from the previous section will be converted to a set of linear equality and inequality constraints by using the relationships shown in Table 3.2.

Table 3.2. Constraint representation of logic propositions and operators (Biegler et al., 1997).

Logical Relation	**Comments**	**Boolean Expression**	**Representation as Linear Inequalities**
Logical OR		$Y_1 \vee Y_2 \vee ... \vee Y_r$	$y_1 + y_2 + ... + y_r \geq 1$
Logical AND		$Y_1 \wedge Y_2 \wedge ... \wedge Y_r$	$y_1 \geq 1$ $y_2 \geq 1$ $\cdots$ $y_r \geq 1$
Implication	$Y_1 \Rightarrow Y_2$	$\neg Y_1 \vee Y_2$	$1 - y_1 + y_2 \geq 1$
Equivalence	Y_1 if and only if Y_2 $(Y_1 \Rightarrow Y_2) \wedge (Y_2 \Rightarrow Y_1)$	$(\neg Y_1 \vee Y_2) \wedge (\neg Y_2 \vee Y_1)$	$y_1 = y_2$
Exclusive OR	Exactly one of the variables is true	$Y_1 \veebar Y_2 \veebar ... \veebar Y_r$	$y_1 + y_2 + ... + y_r = 1$

After applying Table 3.2 to Equations (3.59) to (3.62), the derived logical constraints for nodes in the superstructure are:

$$S1_j - D_j - C_j \leq 0 \tag{3.63}$$

$$D_j - S1_j - C_j - P_j \leq 0 \tag{3.64}$$

$$C_j - S1_j - D_j - P_j \leq 0 \tag{3.65}$$

$$P_j - D_j - C_j \leq 0 \tag{3.66}$$

For example, in Equation (3.63), the meaning for this constraint is “if $S1_j = \text{True or } 1$, there must be at least one unit in a superstructure whether a drying (D_j), a cooling (C_j) or a tempering (P_j) unit in pass j^{th}.

Using the same procedure as applied to nodes in the superstructure, the following constraints for logical relation between nodes and arcs were obtained:

$$v1_j - S1_j \leq 0 \tag{3.67}$$

$$v1_j - D_j \leq 0 \tag{3.68}$$

$$v2_j - S1_j \leq 0 \tag{3.69}$$

$$v2_j - C_j \leq 0 \tag{3.70}$$

$$v3_j - D_j \leq 0 \tag{3.71}$$

$$v3_j - C_j \leq 0 \tag{3.72}$$

$$v4_j - D_j \leq 0 \tag{3.73}$$

$$v4_j - P_j \leq 0 \tag{3.74}$$

$$v5_j - C_j \leq 0 \tag{3.75}$$

$$v5_j - P_j \leq 0 \tag{3.76}$$

$$v6_j - P_j \leq 0 \tag{3.77}$$

$$S1_j - v1_j - v2_j \leq 0 \tag{3.78}$$

$$D_j - v1_j \leq 0 \tag{3.79}$$

$$D_j - v3_j - v4_j \leq 0 \tag{3.80}$$

$$C_j - v2_j - v3_j \leq 0 \tag{3.81}$$

$$C_j - v5_j \leq 0 \tag{3.82}$$

$$P_j - v4_j - v5_j \leq 0 \tag{3.83}$$

Apart from the logical constraints which were derived from the connectivity represented in the superstructure, the following logical constraints are also considered as a part of problem specification.

At a dummy splitting node ($S1_j$), at most one outlet moisture content is allowed from a dummy splitter in each pass j, so that the following logical constraint will be added:

$$v1_j + v2_j \leq 1 \tag{3.84}$$

At a drying unit (D_j), at most one outlet moisture content is allowed from a drying unit in each pass j, so that the following logical constraint will be added:

$$v3_j + v4_j \leq 1 \tag{3.85}$$

At a cooling unit (C_j), at most one inlet moisture content is allowed to a cooling unit in each pass j^{th}, so that the following logical constraint will be added:

$$v2_j + v3_j \leq 1 \tag{3.86}$$

At a tempering unit (P_j), at most one inlet moisture content is allowed to a tempering unit in each pass j, so that the following logical constraint will be added:

$$v4_j + v5_j \le 1 \tag{3.87}$$

3.3.3 Development of disjunctive constraints

In this section, we are dealing with a construction of disjunctive parts in GDP formulation which represents the discrete decisions in the continuous space. For our synthesis problem the disjunction is required for the following decisions:

- Total number of passes
- A stage of inlet moisture contents
- Process models

As explained before, there is a need to transform a disjunctive part into an algebraic form (MINLP model) and the Big-M constraints technique will be considered here.

Considering the disjunction term as appear in Equation (3.6) and (3.11),

$$\bigvee_{i \in I_k} \begin{bmatrix} Y_{ik_j} \\ h_{ik_j}(x_j) \le 0 \end{bmatrix} \qquad ; \forall i \in I, \forall j \in J, \forall k \in K \tag{3.88}$$

By replacing Boolean variables Y_{ik_j} by binary variables y_{ik_j}, the big-M constraints of Equation (3.88) is:

$$h_{ik_j}(x_j) \le M_{ik_j}(1 - y_{ik_j}) \qquad ; \forall i \in I, \forall j \in J, \forall k \in K \tag{3.89}$$

$$\sum_{i \in I_k} y_{ik_j} = 1 \qquad ;\forall j, \forall k \qquad (3.90)$$

$$x_j \in R_+^n, y_{ik_j} \in \{0,1\} \qquad ;\forall i \in I, \forall j \in J, \forall k \in K \qquad (3.91)$$

where the tightest values of M_{ik_j} can be calculated from (Vecchietti et al., 2003):

$$M_{ik_j} = \max\left\{h_{ik_j}(x_j) \middle| x^L \le x \le x^U\right\} \qquad (3.92)$$

Note that Equation (3.89) will become redundant constraints when $y_{ik_j} = 0$.

3.3.3.1 Disjunction for a total number of passes

As we stated before, multi-passes drying processes are required for drying rice due to delicate characteristic of rice grain to moisture gradient. Therefore, the decision which must be made here is the existence of pass $j+1^{th}$ (discrete decision). If the outlet moister content ($Mout_j$) from pass j^{th} is greater than the desired final moisture content (M_f), there will be an existing of pass $j+1^{th}$. From Figure 3.3, since the existence of each pass j^{th} is directly related to the value of binary variable $S1_j$ so that the disjunction to decide whether pass $j+1^{th}$ will exist or not also related to binary variable $S1_j$ as follows:

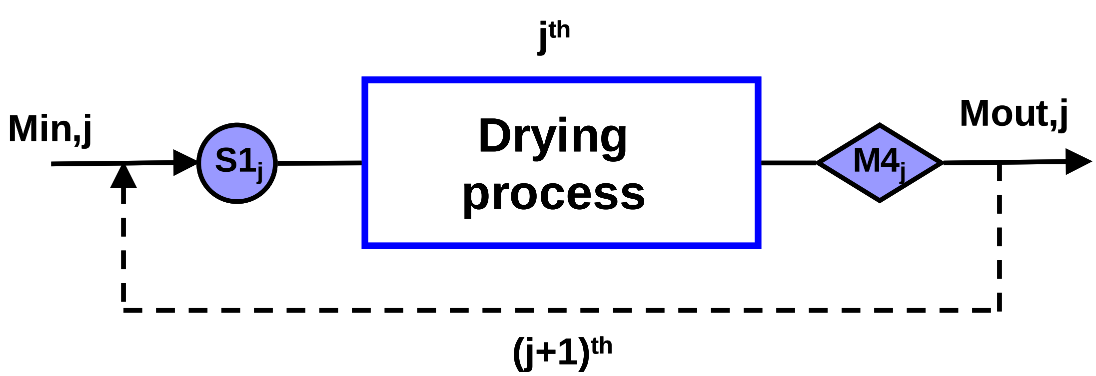


Figure 3.3. Input and output moisture content to a drying process in each pass.

$$\begin{bmatrix} S1_{j+1} \\ Mout_j \geq M_f \\ Min_{j+1} = Mout_j \end{bmatrix} \vee \begin{bmatrix} \neg S1_{j+1} \\ Mout_j < M_f \\ Min_{j+1} = 0 \end{bmatrix} \tag{3.93}$$

By using Big-M constraint for a disjunction in Equation (3.93), the equality and inequality constraints are:

$$M_f - Mout_j \leq (1 - S1_{j+1}) \tag{3.94}$$

$$Min_{j+1} = Mout_j S1_{j+1} \tag{3.95}$$

3.3.3.2 Disjunction for a stage of inlet moisture content

In this section, a disjunction part is used to define the stage of the inlet moisture content ($mDin_j$, $mCin_j$ and $mPin_j$) to each process unit in pass j^{th} which depend on the existence of connectivity between nodes (arcs) in the superstructure. The disjunctive parts for assigning a stage of inlet moisture content to each unit are as follows.

<u>Inlet moisture content to a drying unit</u>:

The only possible source of inlet moisture content to drying unit $(mDin_j)$ is from the arc $v1_j$; therefore the disjunction is:

$$\begin{bmatrix} v1_j \\ mDin_j = Min_j \end{bmatrix} \vee \begin{bmatrix} \neg v1_j \\ mDin_j = 0 \end{bmatrix} \tag{3.96}$$

Such that, the algebraic constraint is:

$$mDin_j = Min_j v1_j \tag{3.97}$$

Inlet moisture content to a cooling unit:

There are 2 sources of inlet moisture content to a cooling unit ($mCin_j$). The first one is the arc $v2_j$ which relates inlet moisture content of pass j^{th} (Min_j) to $mCin_j$. The second one is arc $v3_j$ which relates outlet moisture content from a drying unit ($mDout_j$) to $mCin_j$. Therefore, the disjunction is:

$$\begin{bmatrix} v2_j \\ mCin_j = Min_j \end{bmatrix} \vee \begin{bmatrix} v3_j \\ mCin_j = mDout_j \end{bmatrix} \tag{3.98}$$

Such that, the algebraic constraints is:

$$mCin_j = Min_j v2_j + mDout_j v3_j \tag{3.99}$$

Inlet moisture content to a tempering unit:

There are 2 sources of inlet moisture content to a tempering unit ($mPin_j$). One is arc $v4_j$ which relates outlet moisture content from a drying unit ($mDout_j$) to $mPin_j$. Another one is arc $v5_j$ which relates outlet moisture content from a cooling unit ($mCout_j$) to $mPin_j$. Therefore, the disjunction is:

$$\begin{bmatrix} v4_j \\ mPin_j = mDout_j \end{bmatrix} \vee \begin{bmatrix} v5_j \\ mPin_j = mCout_j \end{bmatrix} \tag{3.100}$$

Such that, the algebraic constraints is:

$$mPin_j = mDout_j v4_j + mCout_j v5_j \tag{3.101}$$

3.3.3.3 Disjunction for process models

Since no such drying model which can suit any kind of existing drying systems exists; many literature models have been developed under certain experimental conditions for different ranges of drying operations found in the rice drying industry. For this reason, disjunctive constraints are exploited to express alternative choices of drying models which are valid under different operating conditions.

In this work, two drying models ("*drying model 1*" and "*drying model 2*") are considered as choices of drying models for a dryer. To develop the disjunction, we will assign binary variable $yD1_j$ and $yD2_j$ to represent the choice of drying models. If variable $yD1_j$ is equal to 1, *drying model 1* will be selected for a dryer otherwise $yD2_j$ will be equal to 1 and *drying model 2* will be selected. Therefore, the disjunction term for selecting the drying model is as follows:

$$\left[\begin{array}{c} \mathrm{D_j} \\ \\ mDin_j \geq 0 \\ \left[\begin{array}{c} yD1_j \\ \text{Drying model 1} \\ TD1^{L} \leq T_{D\,j} \leq TD1^{U} \\ RHD1^{L} \leq RH_{D\,j} \leq RHD1^{U} \end{array}\right] \vee \left[\begin{array}{c} yD2_j \\ \text{Drying model 2} \\ TD2^{L} \leq T_{D\,j} \leq TD2^{U} \\ RHD2^{L} \leq RH_{D\,j} \leq RHD2^{U} \end{array}\right] \end{array}\right] \vee \left[\begin{array}{c} \neg \mathrm{D_j} \\ \\ mDin_j = 0 \\ \\ \end{array}\right] \tag{3.102}$$

From Equation (3.102), the derived equality and inequality constraints are:

$$(mDin_j)Dj \geq 0 \tag{3.103}$$

$$D_j = yD1_j + yD2_j \tag{3.104}$$

$$yD1_j + yD2_j \leq 1 \tag{3.105}$$

$$TD1^{L}\, yD1_{j} \le T_{D\,j} \le TD1^{U}\, yD1_{j} \tag{3.106}$$

$$RHD1^{L}\, yD1_{j} \le RH_{D\,j} \le RHD1^{U}\, yD1_{j} \tag{3.107}$$

$$TD2^{L}\, yD2_{j} \le T_{D\,j} \le TD2^{U}\, yD2_{j} \tag{3.108}$$

$$RHD2^{L}\, yD2_{j} \le RH_{D\,j} \le RHD2^{U}\, yD2_{j} \tag{3.109}$$

Equation (3.106) to (3.109) showed that drying operations, which is temperature and relative humidity of drying air, are bounded under two valid ranges of drying models. $TD1^{L}$ and $TD1^{U}$ is lower and upper bound of valid range of drying temperature for "*drying model1*", $RHD1^{L}$ and $RHD1^{U}$ is lower and upper bound of valid range of relative humidity for "*drying model1*", $TD2^{L}$ and $TD2^{U}$ is lower and upper bound of valid range of drying temperature for "*drying model2*", and $RHD2^{L}$ and $RHD2^{U}$ is lower and upper bound of valid range of relative humidity for "*drying model2*", respectively.

3.4 Case Study

To illustrate the application of GDP to the synthesis problem, three case studies were chosen to investigate different aspect of benefit of using the GDP model to tackle with different proposed drying models in the synthesis problem. Also, as stated before, in every case study, the solution of the synthesis problem will be investigated under two objective criteria: maximization of head rice yield and minimization of energy consumption. The optimum solutions obtained from the synthesis problem considered here consist of the followings:

- Total number of passes required for drying rice from initial moisture content (M_i) to final moisture content (M_f).
- Flowsheet configuration to specify the existence of unit operations in each pass (j) whether a drying (D_j), a cooling (C_j), a tempering (P_j), or a combination of them.

- Operating conditions for the existing unit operations in the flowsheet in each pass. Drying temperature ($T_{D\,j}$), relative humidity of drying air ($RH_{D\,j}$) and drying time ($t_{D\,j}$) are for a drying unit. Cooling temperature ($T_{C\,j}$), relative humidity of cooling air ($RH_{C\,j}$) and cooling time ($t_{C\,j}$) are for a cooling unit. Finally, tempering time ($t_{P\,j}$) is for a tempering unit.

3.4.1 Case study 1

This case study was first considered in the work of Phongpipatpong and Douglas (2003b) as MINLP model. However, the difference here is the conditional constraints applied to the problem as noted in section 3.2. The objective of this case study is to study the results from solving two MINLP models derived from different approaches for the same synthesis problem. One MINLP model is developed in an ad hoc basis as found in Phongpipatpong's work (2002) and this model will be named as an "*ad hoc model*". Another MINLP model is developed from the GDP framework as shown in section 3.3 and it will be named as a "*GDP model*". The process models employed for this case study for a drying, a cooling and a tempering unit were from Phongpipatpong and Douglas (2003a) as shown in Equation (3.19) to (3.27). The valid ranges of operating conditions for the models were summarized in Table 3.3. It should be noted that the benefit of using Phongpipatpong and Douglas's models (2003a) for the synthesis problem is that they were developed to predict the drying rate in wide range of operating conditions found in drying processes and to overcome numerical difficulties that occur in solving the synthesis problem.

Table 3.3. Bound of operating conditions from Phongpipatpong and Douglas's model (2003a).

Variable	Lower bound	Upper bound
Drying air temperature (^{O}C)	35	150
Drying air relative humidity (%, decimal)	0.05	0.65
Cooling air temperature (^{O}C)	15	30
Cooling air relative humidity (%, decimal)	0.4	0.6
Drying time (hrs)	0	2
Cooling time (hrs)	0	6
Tempering time (hrs)	0	30

3.4.2 Case study 2

From the previous case study, the simplified models were developed from regression analysis of generated data from proposed literature models (Phongpipatpong and Douglas, 2003a). The purpose of the development of the models was to reduce numerical complexity of the synthesis problem arising from using the developed empirical model in the general from of Page's model as shown in Equation (3.14); however, no experimental work was undertaken to validate the models. Therefore, in this case study our attention is paid to the synthesis problem using empirical drying models which were verified with the experimental data. Nevertheless, their validity only limit in a small range which the models were developed and models are in the form of more complicated mathematical functions when compared to the models applied in Case study 1.

In this case study, the Wang and Singh (1978)'s model was selected as a process model for a drying unit, Basunia and Abe (1998)'s model for a cooling unit, and Phongpipatpong and Douglas (2003a)'s model for a tempering unit. The valid ranges of operating conditions for the models were concluded in Table 3.4.

Table 3.4. Bound of operating conditions used for Case study 2 for the synthesis problem with empirical models.

Variable	Lower bound	Upper bound
Drying air temperature (^{O}C)	35	55
Drying air relative humidity (%, decimal)	0.15	0.85
Cooling air temperature (^{O}C)	11.8	30
Cooling air relative humidity (%, decimal)	0.37	0.91
Drying time (hrs)	0	6
Cooling time (hrs)	0	12
Tempering time (hrs)	0	30

3.4.3 Case study 3

The objective of this case study is to exploit a disjunction part of a GDP model to integrate alternative choices of various empirical drying models which are valid under different ranges of drying operations in the synthesis problem. This study was inspired from the fact that many thin-layer drying models are available for a drying simulation at present but most of them were developed and validated under a specific range of experimental conditions which limit their application. In this case study, two drying models which are valid in different ranges of operating conditions will be considered in a GDP model to extend the ability of synthesis problem for the analysis of drying processes in a wider range of drying operation found in a real drying system. The first one is drying model developed by Wang and Singh (1978) and this model will be named as "*drying model 1*". The second one is the model developed by Phongpipatpong and Douglas (2003a) and this model will be named as "*drying model 2*". Drying model 1 will be employed for predicting the drying rate when the operating temperature of drying units falls in the range of temperature level between 35 and 55 ^{O}C while drying model 2 for operating temperature in the range of temperature level between 55 and 150 ^{O}C. The other process models (for a cooling and tempering unit) employed in this case study will be the same as in Case Study 1. Table 3.4 shows the valid ranges of operating conditions of process models used in this Case study.

Table 3.5. Bound of operating conditions used for Case study 3 for the synthesis problem with empirical models.

Variable	Lower bound	Upper bound
Drying air temperature of drying model 1 (^{O}C)	35	55
Drying air temperature of drying model 2 (^{O}C)	55	150
Drying air relative humidity of drying model 1 (%, decimal)	0.15	0.85
Drying air relative humidity of drying model 2 (%, decimal)	0.05	0.65
Cooling air temperature (^{O}C)	15	30
Cooling air relative humidity (%, decimal)	0.4	0.6
Drying time of drying model1 (hrs)	0	6
Drying time of drying model 2 (hrs)	0	2
Cooling time (hrs)	0	6
Tempering time (hrs)	0	30

3.5 Results and Discussions

In every case study, the synthesis problems which were stated in GDP form will be transformed into an MINLP model as described in Section 3.3. Then, all the problems were coded and solved in

GAMS (Brook et al., 1998) on Intel Core 2 Duo 1.86 GHz PC with 2GB memory using XP operating system. GAMS/DICOPT, based on the outer-approximation (OA) method was used to solve all the problems posted as MINLP models. The reported of the computational experience in using DICOPT to solve MINLP problems arose in process synthesis problem can be found in Kocis and Grossmann (1989). GAMS/MINOS was used for NLP solver and GAMS/CPLEX was used for MILP solver. Note that due to the nonlinearity of models applied here, the optimum solutions found in each case study are not the global optimum. They are the best solutions (local solutions) found among the solutions found from using different initial guesses.

3.5.1 Case study 1

3.5.1.1 Maximization of head rice yield

The result of the optimum flowsheet and its operating conditions from the GDP model when the objective is to maximize the head rice yield is shown in Figure 3.4. Eight passes with the sequence of drying-cooling-tempering units for the first two passes and cooling-tempering units for the others are required to dry rice from initial moisture (34% d.b.) content to the target moisture content (14%d.b.) The % moisture reduction in each pass is 5.5, 4.7, 2, 1.8, 1.7, 1.6, 1.4, and 1.3 respectively. The total operating time at drying units are 1.95 hrs, cooling units are 9.31 hrs and tempering units are 61.21 hrs. The maximum head rice yield is 66.87%.

For the ad hoc model, the optimum flowsheet and its operating conditions when the objective is to maximize the head rice yield is shown in Figure 3.5. The same total number of passes is required as in the case of the GDP model. Nevertheless, the flowsheet configuration is different. The sequence of drying-cooling-tempering units exists in pass numbers 1, 2, 3, 6, 7 and 8 as well as the sequence of cooling-tempering units in pass numbers 4 and 5. The % moisture reduction in each pass is 4.2, 3.6, 3.2, 1.8, 1.8, 1.8, 1.8, and 1.8 respectively. The total operating time at drying units are 2.23 hrs, cooling units are 6.17 hrs and tempering units are 81.88 hrs. The maximum head rice yield is 66.88%.

The optimum drying strategies obtained from both MINLP models for the case of maximizing head rice yield were different even if the same total number of passes was used. From the results of % moisture reduction in each pass, the drying strategy given from the GDP model dried rice is very fast in the first two passes in the drying and cooling units and then it will gradually dry rice for the remaining passes in cooling units only while the drying strategy given from the ad hoc model was milder but required more passes through the dryer. As a result, the drying strategies obtained from the ad hoc model can find a bit better solution of head rice yield.

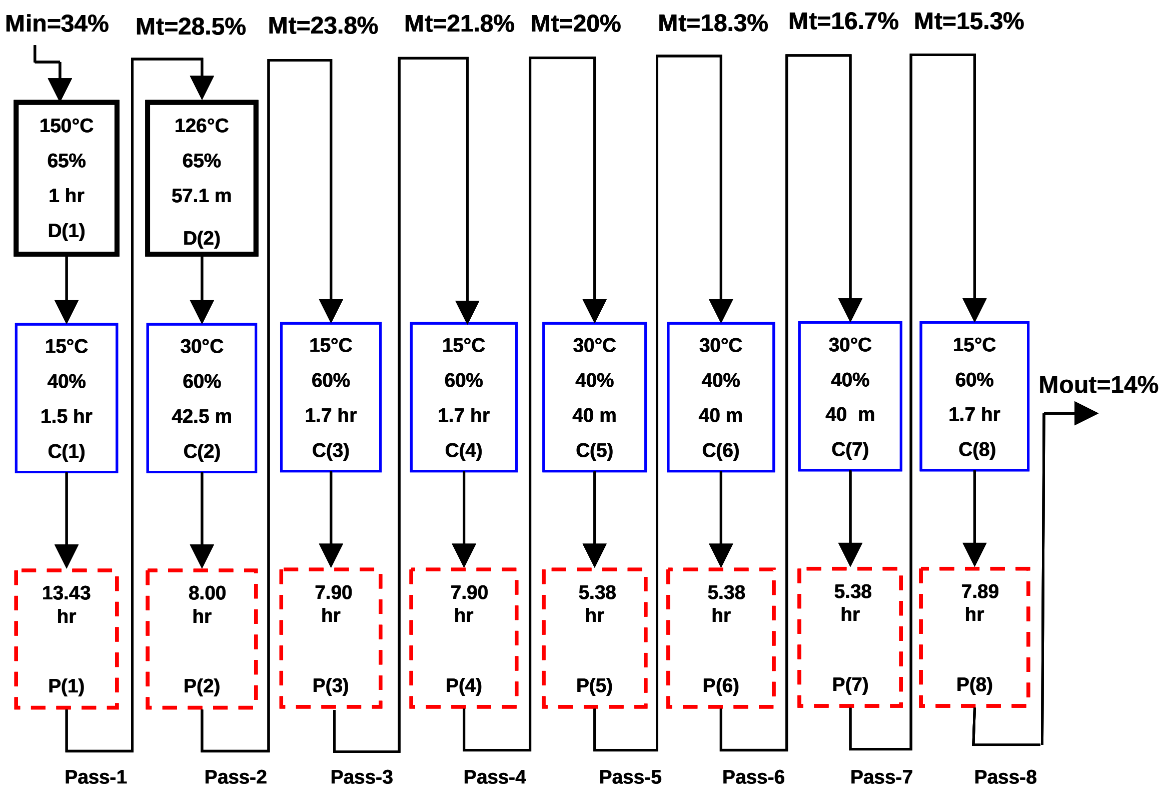


Figure 3.4 The optimal flowsheet of maximization of HRY with the GDP model from Case study 1.

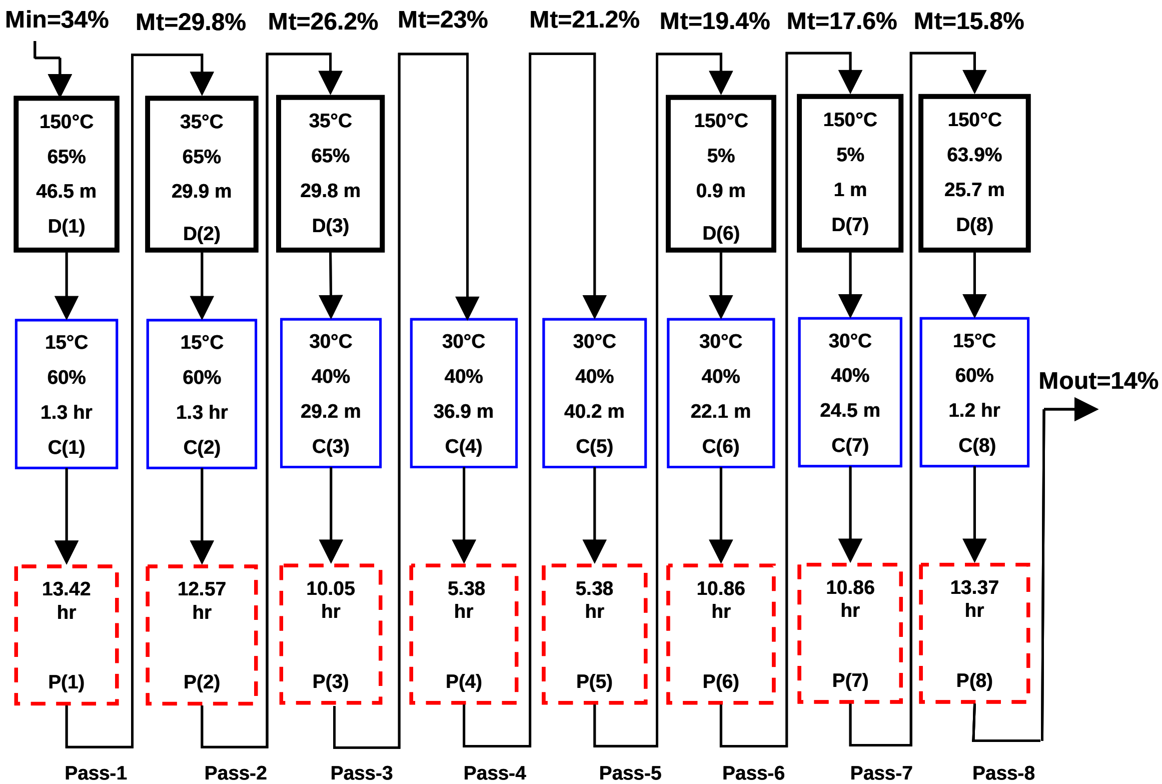


Figure 3.5 The optimal flowsheet of maximization of HRY with the ad hoc model from Case study 1.

3.5.1.2 Minimization of energy consumption

The result of the optimum flowsheet and its operating conditions from GDP model when the objective is to minimize the energy consumption is shown in Figure 3.6. Four passes with the sequence of cooling-tempering units are required to dry rice from initial moisture (34% d.b.) content to the target moisture content (14%d.b.) The moisture reduction in all passes is 5% (d.b.). The total operating time at cooling units are 6.9 hrs and tempering units are 21.64 hrs. The minimum energy consumption is 3 MJ/kg of water removed.

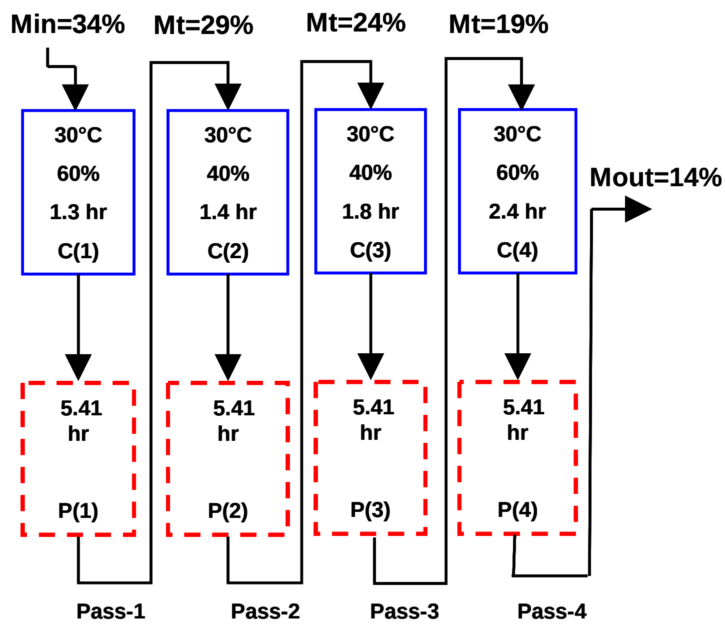


Figure 3.6 The optimal flowsheet of minimization of energy consumption with the GDP model from Case study1.

For the ad hoc model, the result of the optimum flowsheet and its operating conditions is shown in Figure 3.7. The same total number of passes and flowsheet configuration are obtained as in the case of the GDP model to dry rice from an initial moisture (34% d.b.) content to the target moisture content (14%d.b.). The moisture reduction in all passes is 5% (d.b.). The total operating time at cooling units is 6.9 hrs and tempering units is 21.63 hrs. The minimum energy consumption is 3 MJ/kg of water removed.

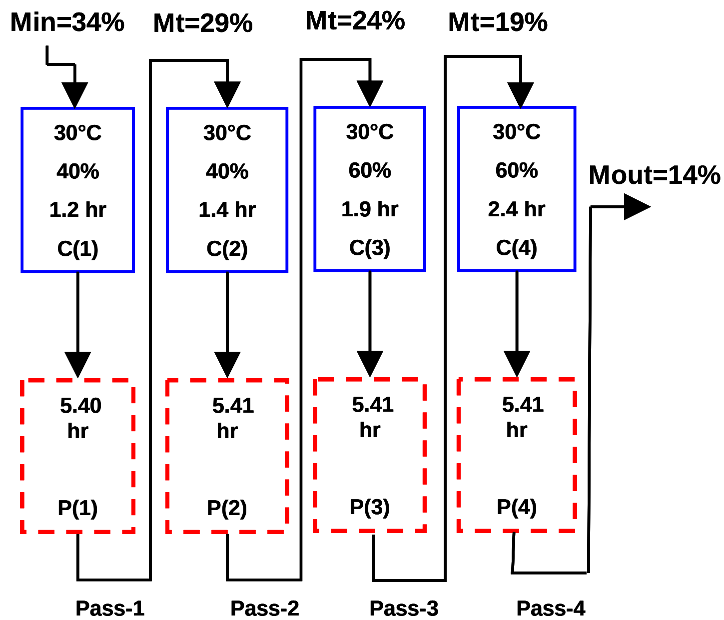


Figure 3.7 The optimal flowsheet of minimization of energy consumption with the ad hoc model from Case study1.

For the case of minimum energy consumption, both models gave the same total number of passes and flowsheet configuration. Moreover, operating levels from both drying systems is the same which use the lowest allowable temperature of cooling units at 30^{o}C to dry rice. Therefore, the minimum energy consumption is the same (3 MJ/kg of water removed)

3.5.2 Case study 2

3.5.2.1 Maximization of head rice yield

The result of the optimum flowsheet and its operating conditions when the objective is to maximize the head rice yield is shown in Figure 3.8. Eight passes with the sequence of drying-cooling-tempering units for all passes except at pass 3 with the sequence of drying-tempering are required to dry rice from initial moisture (34% d.b.) content to the target moisture content (14%d.b.). The % moisture reduction in each pass is 4.1, 3.5, 2.9, 2.5, 2.2, 1.9, 1.5, and 1.4 respectively. The maximum head rice yield is 69.88%.

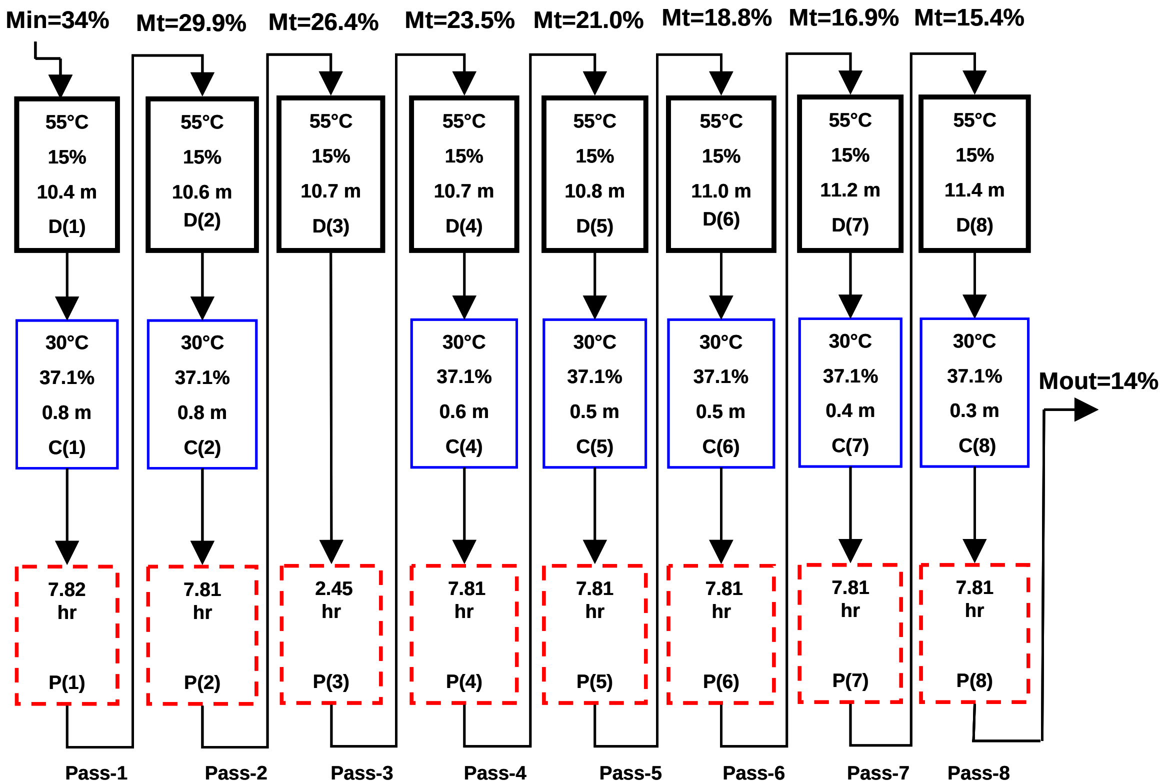


Figure 3.8 The optimal flowsheet of maximization of HRY from Case study 2.

The optimum drying strategy obtained in each pass is quite the same which is operated at the maximum allowable temperature level and lowest relative humidity in both drying and cooling units. The operating time spent in a drying unit is increasing as the number of the passes increases even though the % moisture reduction in each pass keeps decreasing. This is because of the fact that more effort is needed to draw out the moisture from the grain when the grain starts losing more moisture. It should be noted that Basunia and Abe's model (1998) was developed under low temperature conditions for the thin-layer drying experiment in the range for 4 to 6 days (96 hrs to 144 hrs). Therefore, their model is suitable in the prediction of very slow drying operations. This is probably the reason that the optimum operating time obtained in cooling units is almost insignificant because drying is too slow compared to the Wang and Singh's model. Basunia and Abe (1998) recommended that their model is suitable for ambient in-store drying system.

3.5.2.2 Minimization of energy consumption

The result of the optimum flowsheet and its operating conditions when the objective is to minimize the energy consumption is shown in Figure 3.9. Six passes with the sequence of cooling-tempering are required to dry rice from initial moisture (34% d.b.) content to the target moisture content (14%d.b.). The % moisture reduction in each pass is 6, 6, 2, 2, 4, and 4 respectively. The total operating time at cooling units is 57.2 hrs and tempering units is 33.26 hrs. The minimum energy consumption is 3 MJ/kg of water removed.

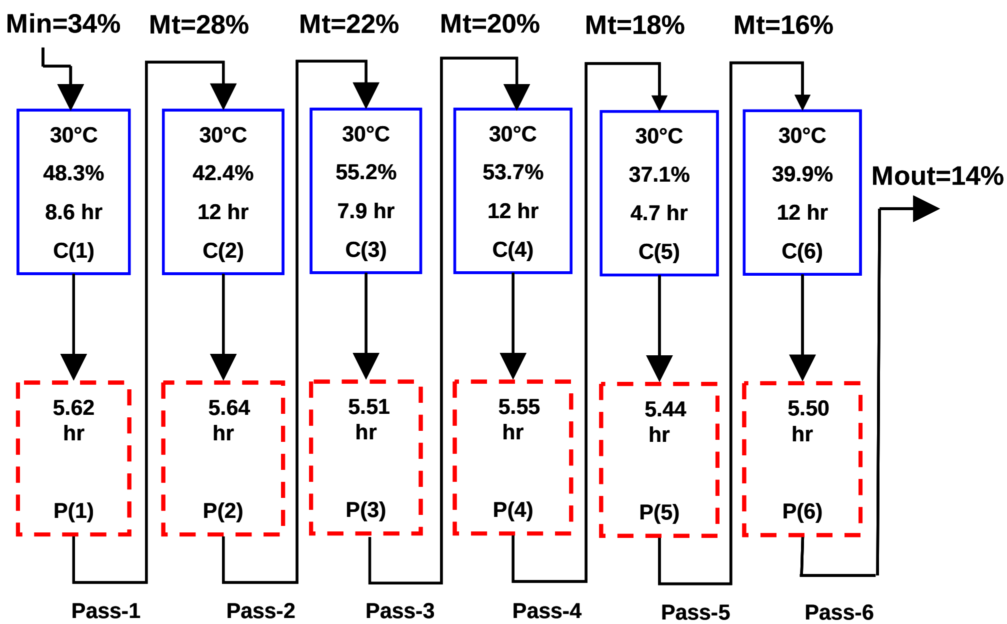


Figure 3.9. The optimal flowsheet of minimization of energy consumption from Case Study 2.

The drying strategy obtained here is the same strategy obtained from the previous case study. The sequence of cooling-tempering units was used in each pass at the lowest allowable temperature of cooling units (30^{o}C) due to the fact that the energy function is a function of operating temperature only. However, since the cooling model (Basunia and Abe, 1998) employed in this case study was developed for a very slow drying operation; as a result a very long operating time as well as more number of unit operations were required to dry rice when compared to the models used in Case study 1.

3.5.3 Case study 3

3.5.3.1 Maximization of head rice yield

The result of the optimum flowsheet and its operating conditions when the objective is to maximize the head rice yield is shown in Figure 3.10. Eight passes with the sequence of drying-tempering units are required to dry rice from initial moisture (34% d.b.) content to the target moisture content (14%d.b.). The model which was selected to explain the drying rate is "*model 1*" for all passes. The % moisture reduction in each pass is 4.1, 3.5, 3, 2.5, 2.2, 1.8, 1.6, and 1.3 respectively. The maximum head rice yield is 69.87%

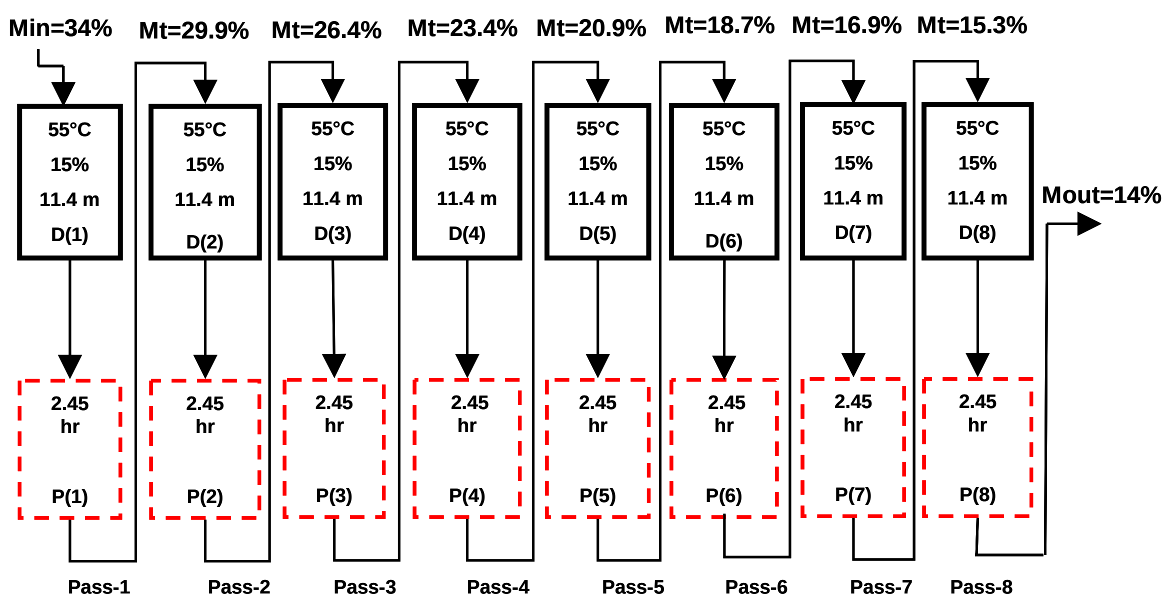


Figure 3.10. The optimal flowsheet of maximizing of HRY from Case Study 3.

The reason that "*drying model 1*" developed by Wang and Singh (1978) was selected because when we compared the drying rate predicted by all the models employed in this case study (Wang and Singh's model (1978) for a drying unit and Phongpipatpong and Douglas's models (2003a) for a drying and a cooling unit), drying rate predicted from Wang and Singh's model gave the slowest rate as shown in Figure 3.11. As we know, slow drying is a favourable condition to maintain the quality of rice (HRY) due to the reason that it develops less moisture gradient within a rice grain when compared to the fast drying rate.

In Figure 3.11, the moisture ratio calculated from Wang and Singh's model for a drying unit ("*drying model 1*"), Phongpipatpong and Douglas's models for a drying unit ("*drying model 2*") and a cooling unit (cooling model) were plotted versus the operating time (minute). The selected operating conditions to calculate the moisture ratio for each model are given in Table 3.6.

Table 3.6. Selected level of operating conditions for each model as shown in Figure 3.11.

	Temperature (^oC)	Relative humidity (%)	Remark
Drying model 1	55	15	Optimum operating levels found from Case study 3
Drying model 2	35	65	Slowest drying rate condition of "*drying model 2*"
Cooling model	15	60	Slowest drying rate conditions of the cooling model

As note in Table 3.6, the criteria for selecting the operating conditions of "*drying model 2*" and cooling model were based on the allowable conditions which give the slowest drying rate for each model.

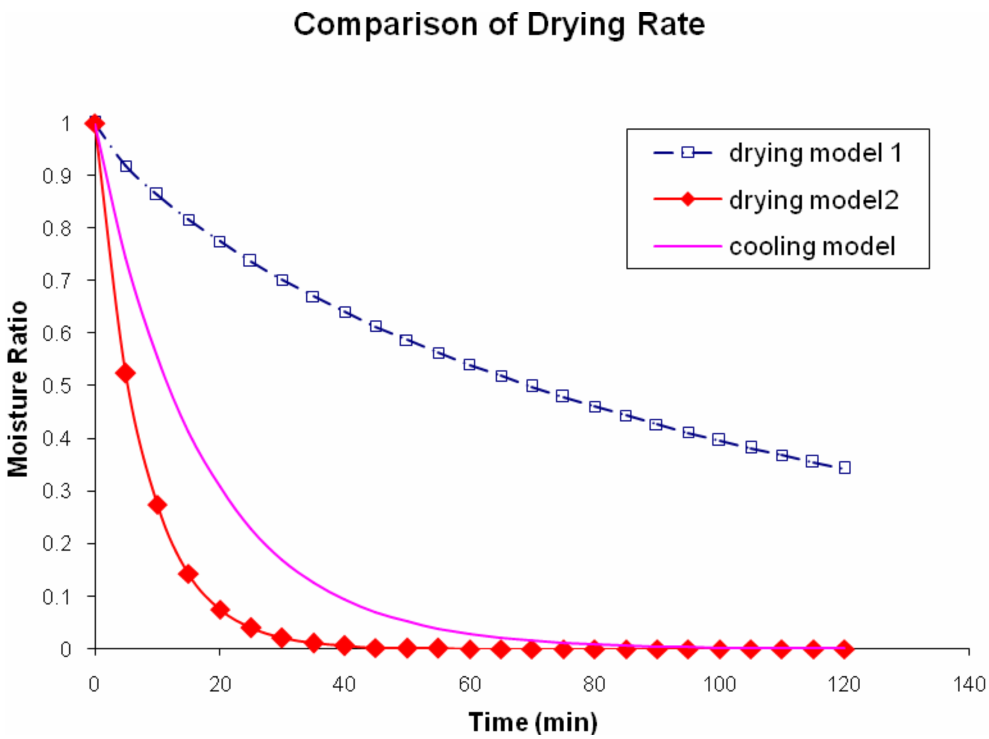


Figure 3.11. The comparison of drying rate from using different drying and cooling models.

3.5.3.2 Minimization of energy consumption

The result of the optimum flowsheet and its operating conditions when the objective is to minimize the energy consumption is shown in Figure 3.12. No drying unit was selected to do the drying task. Only cooling and tempering units were selected due to the same reason as discussed in the other case studies that optimum operating temperature of cooling unit found here is lower than the lowest operating temperature allowed in a drying unit. Since the cooling model employed here is the same as the cooling model used in Case study 1; therefore, quite the same optimum drying strategy found from Case study 1 was obtained here in the case of minimizing the energy consumption. Four passes with the sequence of cooling-tempering are required to dry rice from an initial moisture (34% d.b.) content to the target moisture content (14%d.b.). The % moisture reduction in each pass is 6, 6, 4 and 4 respectively. The total operating time at cooling units is 6.8 hrs and at tempering units is 21.64 hrs. The minimum energy consumption is 3 MJ/kg of water removed.

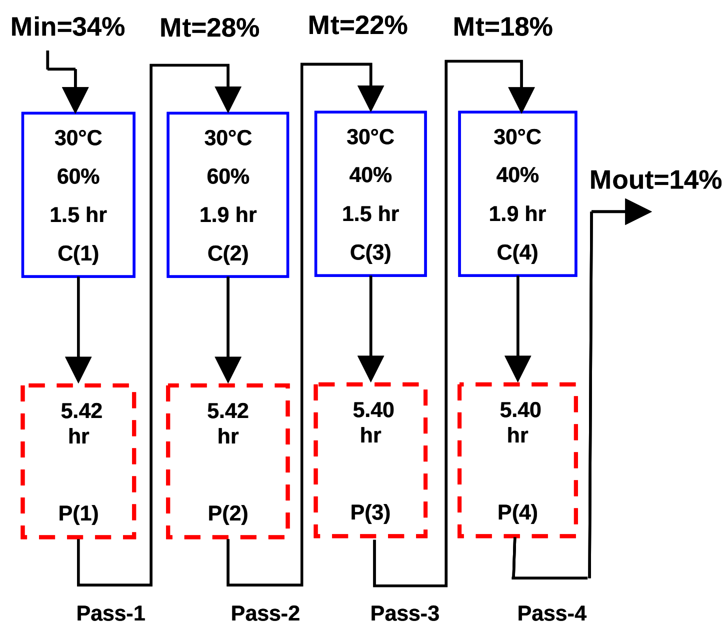


Figure 3.12. The optimal flowsheet of minimizing of energy consumption from Case Study 3.

3.5.4 Comparison between the case studies

The optimum results obtained from different case studies will be compared in this section in the aspects of problem formulation, the optimum solutions obtained and the calculation time from using different drying models for the synthesis problem of rice drying processes. The optimization results from all case studies are given in Table 3.7.

From Table 3.7, the MINLP based GDP formulation of Case study 3 generated the maximum number of equations and variables. However, this formulation is not the one which employed the most calculation time. The maximum calculation time was employed in a case of maximizing HRY in the ad hoc model of Case study 1(406.54 CPUs) although this problem generated the minimum number of equations. Moreover, in Case study 1, the MINLP based GDP model (6.56 CPUs) also significantly spent less computation time than the ad hoc MINLP model (406.54 CPUs) even though all the models employed for both problems in this case study were the same. However, in Case study 1, the CPU time required to solve the MINLP based GDP model (21.70 CPUs) is longer than the CPU time required to solve the ad hoc MINLP model (1.36 CPUs) for the case of energy objective function. In terms of optimum solution, the optimum solutions obtained from using both MINLP models are comparable in both cases (maximum head rice yield and minimum energy consumption) as shown in columns 1 and 2 of Table 3.7 for Case study 1.

Table 3.7 Comparison of the optimization results of all case studies.

Description	Case Study 1 (ad hoc model)		Case Study 1 (GDP model)		Case Study 2 (GDP model)		Case Study 3 (GDP model)	
	HRY	Energy	HRY	Energy	HRY	Energy	HRY	Energy
# of equations	233	233	506	506	602	602	698	698
# of variables	265	265	297	297	345	345	417	417
# of discrete variables	24	24	72	72	72	72	88	88
Total time in drying (hrs)	2.23	-	1.95	-	1.45	-	1.52	-
Total time in cooling (hrs)	6.17	6.9	9.31	6.9	0.07	57.2	-	6.9
Total time in tempering (hrs)	81.88	21.63	61.21	21.64	57.13	33.26	62.5	21.63
% HRY	66.88	66.83	66.87	66.83	69.88	67.45	69.87	66.83
Energy consumption (MJ/kg of water removed)	4.41	3	4.80	3	3.75	3	3.80	3
Total CPU time (s)	**406.54**	**1.36**	**6.56**	**21.70**	**23.77**	**2.21**	**1.53**	**2.54**
NLP:	406.42	1.03	5.82	9.35	3.71	1.45	1.03	1.67
MIP:	0.12	0.33	0.72	12.35	20.06	0.76	0.5	0.87

From this point of view, we found that the MINLP model derived from the GDP framework generated more variables and constraints than the ad hoc MINLP model. However, more variables and constraints was paid off to the better information provided for a variable relationship. This characteristic is very useful in improving the solution strategy for the problem involving complicated or highly nonlinear functions like in the case of maximum head rice yield problem. Nonetheless, for the problem involving simple linear functions like in the case of minimum energy consumption, the MINLP based GDP model did not outperform over the ad hoc MINLP model. It should be noted that the HRY objective function is a nonlinear function of three operating variables which are temperature, relative humidity of drying temperature and drying time while the energy consumption function is a linear function of only drying temperature. Also, in term of quality of optimum solution obtained from using both formulations, none of them outperforms the other. Both formulations converge to a comparable value of objective functions.

In terms of the drying strategy found in each case study, the drying strategy obtained from case study 2 gave the maximum yield of head rice because all the process models employed in this case study can predict the slowest drying rate when compared to the other models used in this work. This results in less moisture gradient developed in the rice grain. The least moisture gradient developed in the grain by the drying process is, the more head rice yield will be preserved. Interestingly, in the case of minimizing energy consumption, all the case studies found the same optimum amount of energy used and quite the same optimum drying strategy (4 passes with the sequence of cooling-tempering units at the operating temperature of 30^{o}C) although different kinds of drying models were employed in each case study. Nevertheless, the maximum processing time spent in cooling units and tempering units was found in case study 2 with the reason that the process model of a cooling unit employed in the case study was developed for ambient in-store drying system. The reason that the same amount of energy was found is that the energy objective function is the function of only operating temperature. Thus, the optimum solutions found in all the case studies employed the minimum level of operating temperature (30^{O}C) which was allowed in the range of models in all case studies.

The optimum strategy which gave the minimum HRY (66.83%) is the drying strategy found in Case studies 1 and 3 with the objective of minimizing the energy consumption. The reason is that both case studies try to find the strategy which can reduce the moisture content to the target moisture content and use minimum amount of energy without considering the effect of drying conditions on the quality of head rice. Moreover, the drying rate predicted by the cooling models employed in these two case studies is faster than the one employed in Case study 2. On the other hand, the optimum strategy which use the maximum amount of energy (4.80 MJ/kg of water removed) to dry rice is the drying strategy found in case study 1 for the GDP model with the objective of maximizing HRY. This is because the problem tried to find the strategy which can gradually reduce the moisture content as much as possible to maintain the quality of head rice without considering the amount of energy which will be used. Therefore, these results leave us with the conclusion that an attempt to lower the energy consumption will result in lowering the quality of head rice while an attempt to higher the quality of head rice will result in increasing the energy consumption.

Different drying strategies were obtained from solving the synthesis problem employed with different empirical models valid in different ranges of drying conditions in case of maximum head rice yield. These results gave us a broader-vision for drying operations. For example, the empirical models employed in Case study 1 give a picture of the optimum drying strategies which are operated in the range of high temperature levels such as Fluidized-bed dryers and mixed-flow dryers. Case studies 2 and 3 give a picture of the optimum drying strategies which are operated in the range of moderate to low temperature levels such as cross-flow dryers and in-bin dryers.

3.6 Conclusion

The synthesis problem of rice drying processes using various empirical drying models under a GDP framework were addressed and investigated with the aid of various case studies. Different drying strategies were obtained from solving the synthesis problem employed with different empirical models. These results gave us a broader-vision for drying operations of rice drying processes.

Using the generalized disjunctive programming (GDP) framework directly and systematically transformed the qualitative (logic) and quantity (equations) information contained in the flowsheet synthesis problem into a mathematical model in a more natural way when compared to an ad hoc model. This provided a better structure of variable relationship between discrete and continuous variables in the problem formulation of the synthesis problem which can improve the search strategy and solution efficiency of the synthesis problem. This characteristic was very useful especially for the problem dealing with highly nonlinear objective functions such as in the case of maximum head price yield. Moreover, because of this good characteristic of MINLP based GDP model, the synthesis problem of rice drying processes dealing with various kinds of empirical models were solved in reasonable time in GAMS. Furthermore, exploitation of the disjunctive part of the GDP model can facilitate the formulation of the synthesis problem containing choices of drying models to eliminate the problem of having proposed empirical models which are valid only in a small range of real drying operations.

Chapter 4
Mixed-Integer Dynamic Optimization for Synthesis of Rice Drying Processes

4.1 Introduction

Synthesis problem of rice drying processes has not been well explored yet due to the craft orientation and conservative background of agricultural industries. Therefore, there is a need for integrated analysis of a drying process to find the best process structure or policy and operating conditions of rice drying plant that yield the best performance (Phongpipatpong, 2002). In the previous chapter, the synthesis problems of rice drying processes were performed based on proposed empirical models from literature resulting in MINLP model; however, aside from their ease of use, empirical models are only valid within their experimental conditions and also there is a need for developing an empirical model for each particular unit operation represented in a rice drying process. For these reasons, the interest of using theoretical model for describing the kinetic of moisture reduction in rice grain in the synthesis problem of rice drying processes is the focus in this chapter. The motivation of this chapter is from the fact that a drying process happening in any unit operations existing in a drying system can be theoretically described by the same coupled heat and mass transfer process. This process is represented by a set of differential algebraic equations (DAEs). Using the theoretical model, there is no need for developing a drying model for each particular unit involved in drying processes. Another issue is that in real drying operation (e.g. fluidized-bed drying system, crossflow dryer), the state of grain (e.g. moisture content and temperature) is changing continuously and it is necessary to take a change of process state (dynamic) into account (Boxtel and Knol, 1996). Again, a theoretical model, which can capture the dynamic behaviour (transient phenomena) of the process, is an alternative choice which can provide more detailed and accurate prediction of drying rate when compare to simplified model.

In the synthesis problem of rice drying processes with theoretical models, it involves a non-linear set of differential-algebraic equations (DAEs) and a discrete set of process alternatives. This problem gives rise to the type of optimization problem called mixed-integer dynamic optimization (MIDO). A MIDO problem is very difficult to solve (Barton and Lee, 2004). Apart from the highly nonlinear and multimodal arising from the part of differential-algebraic equations (continuous part), also the discontinuous part of discrete decisions complicate the solution algorithm.

Currently reported techniques to solve MIDO problem have been found in the class of decomposition approaches (Barton et al., 1998; Allgor and Barton, 1999; Bansal et al., 2003; Oldenburg et al., 2003; Barton and Lee, 2004; Chachuat et al., 2005). The general idea is that the MIDO problem is divided into one master problem and one primal dynamic optimization (DO) problem. The master problem yields a lower bound on the solution and an update for the discrete (binary) variables. Then, the primal problem fixes these discrete variables of the problem and solves for an upper bound on the solution. These two problems will be solved iteratively in a sequence till the upper and lower bounds approach to within the desired tolerance. Different decomposition approaches differ in the way this sequences constructed and in the properties required to ensure the validity of the bounds (Allgor and Barton, 1999). From this decomposition based approach, a derivation of a primal problem is simply done by fixing discrete variables while for a master problem is not a trivial task. It requires the construction of relaxation bounds on objective function, constraints as well as the bounds of time varying state variables which are in the form of differential equations. A detail of techniques for constructing these bounds can be found in (Papamichail and Adjiman, 2002; Singer and Barton, 2006). Nevertheless, Chachuat et al. (2005) stated that no general procedure has been reported yet to solve any MIDO problem and can guarantee global optimality.

In this chapter, we present a hybrid approach that is sufficiently general to follow for various classes of the MIDO problem, and which at the same time avoids the complications that arise in the construction of the bounds on the master problem. The approach which combines genetic algorithms (GAs) and control vector parameterization (CVP) is proposed to solve the MIDO problem encountered in this chapter. Hybrid optimization methods have received increasing interest from many researchers as an alternative method to solve real-world optimization problems due to the fact that they combine and extend the strengths of individual well-developed techniques and at the same time alleviate their weakness (Carrasco and Banga, 1998; Bansal et al., 2002; Banga et al., 2005; Younes et al., 2009). This idea can help developers and users from getting trap in a complication and restriction of existing proposed optimization techniques. An example of studies which employed hybridization methods to solve real-world optimization problem can be found in Shafiei et al. (2004), Banga et al. (2005), Till et al. (2007), and Balsa-Canto et al. (2005).

The remainder of this chapter is organized as follows. In Section 4.2 the synthesis problem of rice drying processes with theoretical models will be addressed. Then, the hybrid approach to solve the resulting MIDO problem is proposed in Section 4.3. The implementation issues related to the application of the proposed method for the synthesis problem is given in Section 4.4. The illustrated case studies of the proposed algorithm to solve the synthesis problem are then presented in Section 4.5 and finally the conclusion of work done in this chapter is shown in Section 4.6.

4.2 The Synthesis Problem of Rice Drying Process with Theoretical Model

As mentioned in the previous chapter the synthesis problem of rice drying processes aims to determine the optimal sequence of process configuration and its operating conditions in each pass of multistage rice drying system to dry rice from initial moisture content to the safe storage level. In this chapter, theoretical models will be used to predict the drying behaviour of rice grain. A theoretical model developed by Abud-Archila et al. (2000a) will be employed in this work. They considered rice grain as two homogeneous compartments (as shown in Figure 4.1)

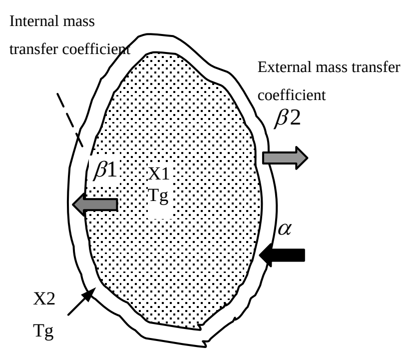


Figure 4.1. Compartmental representation of rice grain ((Abud-Archila et al., 2000b).

They assumed that mass transfer occurs by diffusion only between two compartments and vaporization occurs only at the surface of the rice grain. Heat transfer happens only at the grain surface. The grain temperature is considered uniform and equal for both compartments. The compartmental model is:

$$\frac{dx_1}{dt} = \frac{\beta_1}{\rho_g \cdot \tau_1}(x_2 - x_1) \quad (4.1)$$

$$\frac{dx_2}{dt} = \frac{\beta_2 \cdot S_{sg}}{\rho_g \cdot \tau_2}(p_a - p_g) - \frac{\beta_1}{\rho_g \cdot \tau_2}(x_2 - x_1) \quad (4.2)$$

$$\frac{dT_g}{dt} = \frac{\alpha \cdot S_{sg} \cdot (T_a - T_g) + \beta_2 \cdot S_{sg} \cdot (p_a - p_g) \cdot L_v}{\rho_g \cdot (C_{pg} - C_{pw} \cdot \bar{x})} \quad (4.3)$$

where x_1 and x_2 is the grain moisture contents of compartment 1 and 2 (% d.b.), T_g and T_a are the grain and air temperature (^{o}C), p_g and p_a are the partial vapour pressure at the grain surface and in the drying air (Pa). The partial vapour pressure at the grain surface is defined as:

$$p_g = p_{g\mathrm{sat}} \cdot A_w \quad (4.4)$$

And the water activity A_w is given by

$$A_w = -K_0 \cdot (x_2 - x_1)^5 \cdot \exp\left(\frac{\exp((C_1 - x_2)/C_2)}{C_3 \cdot (T_g - C_4)}\right) \quad (4.5)$$

The saturation vapour pressure at the grain temperature p_{gsat} (Buck, 1981) is

$$p_{gsat} = 6.1121\exp\left[\frac{17.502T_a}{(240.97 + T_a)}\right] \quad (4.6)$$

The mass transfer coefficients between the two compartments (β_1) and between the outer compartment and the air (β_2) are:

$$\beta_1 = \beta_{10} \cdot \exp(B_{11} \cdot \bar{x} \cdot T_g) \quad (4.7)$$

$$\beta_2 = \beta_{20} \cdot \exp(B_{21} \cdot T_a) \tag{4.8}$$

The heat transfer coefficient between the grain surface and the drying air is

$$\alpha = C_5 \cdot L_v \cdot \beta_2 \tag{4.9}$$

The average moisture content of grain computed as a function of the volume fraction of each compartment (τ_1 and τ_2) is:

$$\bar{x} = x_1 \cdot \tau_1 + x_2 \cdot \tau_2 \tag{4.10}$$

The value of parameters and constants for the compartmental model are given in Table 4.1. Note that the compartmental model as shown in Equation (4.1) to (4.10) was developed to predict the drying rate of a single grain kernel. To apply this model in the synthesis problem, the following assumptions have been made:

- Any drying, cooling and tempering units are considered as homogeneous system. Drying behaviour and characteristics of rice grains in the units are the same.

- To simplify the problem, in any position of rice grains in a unit operation, grains are supplied with the same quality of air (air temperature and relative humidity).

- The synthesis problem takes into account only dynamic behaviour of state variables related to a grain phase (i.e., moisture content and grain temperature) while, in air phase, properties of air (i.e. air temperature and relative humidity) are assumed to be constant.

- In drying and cooling units, coupled heat and mass transfer between grain and air phase is considered.

- In tempering units, heat and mass transfer between grain and air phase is negligible (Steffe and Singh, 1980). Only mass transfer between two compartments is considered.

Table 4.1. The parameters and constants of the compartmental model.

Symbol	Description	Value	Units
C_1	Sensitivity coefficients of the water activity with respect to the moisture content in the outer grain compartment	0.319	(kg water) (kg dry matter)$^{-1}$
C_2	Sensitivity coefficients of the water activity with respect to the moisture content in the outer grain compartment	0.0493	(kg water) (kg dry matter)$^{-1}$
C_3	Sensitivity coefficients of the water activity with respect to the grain temperature	1.8994	°C^{-1}
C_4	Sensitivity coefficients of the water activity with respect to the grain temperature	2.5457	°C
C_5	Constant used in equation (4.9) between heat and mass transfer coefficients	65	Pa °C^{-1}
C_{pg}	Specific heat capacity of the dry grain	1300	J (kg dry matter)$^{-1}$ °C^{-1}
C_{pw}	Specific heat capacity of water	4210	J (kg water)$^{-1}$ °C^{-1}
ρ_g	Dry rice density	1500	(kg dry matter) m^{-3}
L_v	Specific heat of vaporization	2.357×10^{6}	J kg^{-1}
S_{sg}	Specific dry grain surface	2000	m^2 m^{-3}
τ_1	Volume fraction of the inner grain compartment	0.6	m^3 m^{-3}
τ_2	Volume fraction of the outer grain compartment	0.4	m^3 m^{-3}
R	Perfect gas constant	8.32	J mol^{-1} K^{-1}
B_{10}	Mass transfer coefficient between the two grain compartments at 0 °C	0.01316	(kg dry matter) m^{-3} s^{-1}
B_{11}	Sensitivity coefficient of the mass transfer between the two grain compartments	0.3083	(kg water), (kg dry matter)$^{-1}$ °C^{-1}
B_{20}	Mass transfer coefficient between the outer grain compartment and the air at 0 °C	2.304×10^{-9}	(kg water) m^{-2} Pa^{-1} s^{-1}
B_{21}	Sensitivity coefficient of mass transfer between the outer grain compartment and air	0.0442	°C^{-1}

In our work, mathematical programming will be used as a tool to solve the synthesis problem, three major steps are required: superstructure representation, problem formulation and solution strategy. In the following section, each step will be described in more details.

4.2.1 Superstructure representation

In this chapter, five alternatives that are found in practice for multistage drying systems are considered: drying-cooling (alternative 1), drying-tempering (alternative 2), cooling-tempering (alternative 3), drying-cooling-tempering (alternative 4), and drying-tempering-cooling (alternative 5). Also, as the name stated, multistage drying system requires more than one pass of drying to prevent the loss of rice quality (head rice yield), by gradually reduce the moisture content in each pass. As a result, the superstructure of rice drying system for the synthesis problem of drying processes using theoretical model is represented in Figure 4.2. Note that the nodes $S1_j$ to $S4_j$ and $M1_j$ to $M4_j$ are dummy splitting and mixing nodes respectively. They do not actually exist in a real drying system but they are introduced for the ease of understanding the connectivity of various units in the superstructure. From Figure 4.2, rice at initial moisture content (M_i) will pass through multi-pass sequence (j) of drying (D_j), cooling (C_j), and/or tempering (P_j) units till the moisture content of rice grain reaches the safe storage level (M_f). Min_j is inlet moisture content to pass j and $Mout_j$ is outlet moisture content from pass j respectively. The specific conditions of rice drying processes considered in this chapter are given in Table 4.2. We set the maximum number of passes to eight. Thus, with five possible alternatives per pass, this superstructure gives rise to 5^8=390,625 possible configurations.

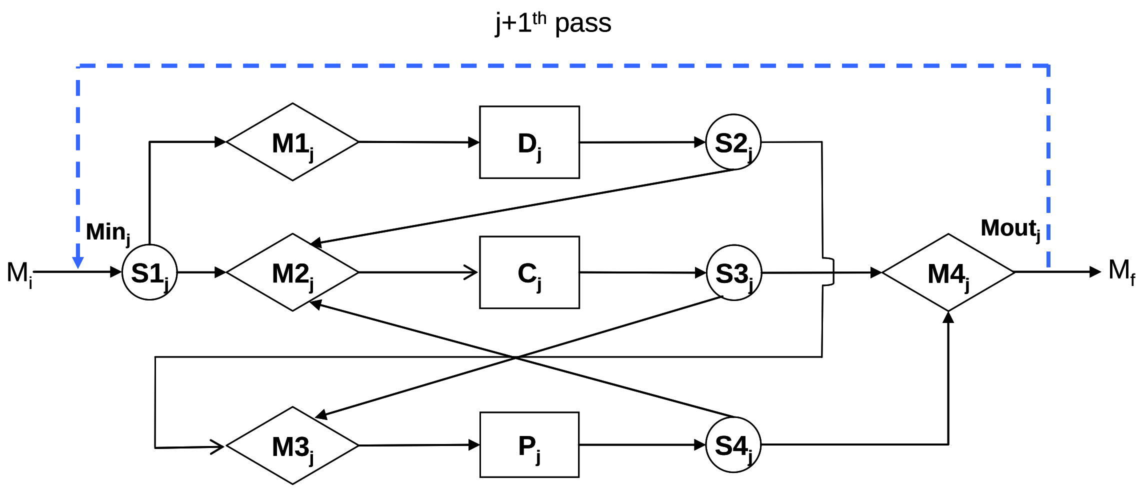


Figure 4.2. Superstructure of rice drying processes with 5 alternatives.

Table 4.2. The specific conditions considered in this work.

Condition	Description
1	Initial moisture content (M_i) is 34% dry basis (d.b.)
2	Maximum number of passes is 8
3	The final moisture content(M_f) should be less than 14% dry basis (d.b.)
4	Maximum head rice yield = 70%

4.2.2 Problem formulation

For the synthesis problem, both discrete and continuous decisions have to be made in order to find the optimal configuration and operating conditions as well as a total number of passes. Also switching of unit operations in each pass leads to a different set of DAEs applied to predict the drying rate. As stated before, in both drying and cooling units, changing of moisture content and temperature of rice grain are taken into account. Therefore, to describe the drying behaviour of rice grain in a drying and a cooling unit, a set of DAEs as shown in Equation (4.1) to (4.10) from the compartmental model will be applied. In a tempering unit, we assumed that rice grain is kept in a closed bin without air flow. There is no heat and mass transfer between grain and air phase (Steffe and Singh, 1980). Only mass transfer between two compartments of rice grain is involved in a tempering bin. Thus, the first term related to the changing of moisture content due to vaporization in Equation (4.2) will be deleted as shown in Equation (4.11). As a result, the set of DAEs to describe the drying behaviour in a tempering unit are Equation (4.1), Equation (4.7), Equation (4.10) and Equation (4.11).

$$\frac{dx_2}{dt} = -\frac{\beta_1}{\rho_g \cdot \tau_2}(x_2 - x_1) \tag{4.11}$$

The synthesis problem considered here involving all the details above gives rise to one class of MIDO called multistage dynamic optimization problem. The general formulation of MIDO problem can be found in Allgor and Barton (1999). In this work we propose the hybrid method which combined GA and CVP approach to solve the MIDO problem encountered in this chapter. In our proposed method, GA will be used to directly search for the optimal configuration of drying system. There is no need for the mathematical formulation for a discrete part of the MIDO problem. Therefore, after fixing the discrete choice of configurations obtained from GA, the synthesis problem reduced to dynamic optimization problem (DO) which involves only the continuous variables. This DO problem will be solved using control vector parameterization (CVP) approach. The detail of the proposed approach will be provided in Section 4.3. Two optimization criteria are considered here: maximization of head rice yield (quality) and minimization of energy consumption. The quality objective function used here is obtained from Abud-Archila et al. (2000b) as shown in Equation (4.12).

$$\frac{dQ}{dt} = -k_0(x_1 - x_2)^5 \exp\left(\frac{-E_a}{R(T_g + 273.1)}\right)Q^2 \tag{4.12}$$

where Q is the quality of rice grain measured in a term of head rice yield (%), k_0 =1.56×10^{27} is the quality degradation rate coefficient (kg water^{-5}kg dry matter^{5} %-1 s^{-1}), and E_a =1.657×10^{5} is the equivalent activation energy for quality degradation kinetic (J mol^{-1}).

For an energy objective function problem, the energy function which was used by Trelea et al. (1997) as a part of optimization criteria in the optimal control problem of batch drying process in corn drying will be employed here. They expressed the function as the rate of change of energy in terms of degrees of rising temperature needed to heat up the air from ambient temperature as shown in Equation (4.13).

$$\frac{dE}{dt} = (T_a - T_{a,amb}) \tag{4.13}$$

where T_a is air temperature and $T_{a,amb}$ is the ambient air temperature (20°C).

Therefore, the DO formulations for two synthesis problems are written mathematically as shown in Equations (4.14) to (4.23).

<u>Maximization of head rice yield</u>:

$$\max_{u(t)} \; Q(t_f) \tag{4.14}$$

Subject to

$f(\dot{x}(t), x(t), u(t), t) = 0$	differential algebraic equations	(4.15)
$x(t_0) = x_o$	initial condition	(4.16)
$\bar{x}(t_f) \le M_f$	point constraint	(4.17)
$u_L \le u \le u_U$	bound of control variables	(4.18)

<u>Minimization of energy consumption</u>:

$$\min_{u(t)} \; E(t_f) \tag{4.19}$$

Subject to

$f(\dot{x}(t), x(t), u(t), t) = 0$	differential algebraic equations	(4.20)
$x(t_0) = x_o$	initial condition	(4.21)
$\bar{x}(t_f) \le M_f$	point constraint	(4.22)
$u_L \le u \le u_U$	bound of control variables	(4.23)

Where $Q(t_f)$ is the yield of head rice at the end of drying process (%), $E(t_f)$ is the energy consumption at the end of drying process, $x(t)$ is the vector of state variables, $\dot{x}$ is the derivative of x with respect to time t, $u(t)$ is the vector of control variables (operating conditions), $\bar{x}(t_f)$ is average moisture content at the final time. Note that Equation (4.15) and (4.20) are a set of different DAEs depending on which unit operation exists in a drying system as explained above.

The similar work of dynamic optimization problem of rice drying process which used quality objective function and the compartmental model developed by Abud-Archila et al. (2000a,b) was studied by Olmos et al. (2002). Their problem aimed to find the optimal control profiles of temperature and relative humidity of drying air which maximize the quality of rice grain in batch drying process. Their problem was constrained by final target moisture content and a fixed operation time. Also, the parameters and constants used in their work are employed in this chapter.

4.2.3 Solution strategy

As stated before, in this work we proposed the hybrid optimization method which combined genetic algorithm (GA) with a control vector parameterization (CVP) approach to solve our synthesis problem. For the proposed method, the MIDO problem will be decomposed into outer integer programming and inner dynamic optimization subproblem. GA will be used to search for discrete part of the problem (an optimum configuration) while CVP will be used to solve for continuous part (dynamic optimization). GA is considered here for solving for the optimum configuration due to the fact that the synthesis problem has a huge total number of possible configurations (5^8= 390,625) in discrete space. The population to population based approach of GAs is effective for global search of a high dimensional combinatorial optimization problem. They sample the search space more effectively and are less apt to getting trapped in a local optima when compare with methods which proceed from point to point (Younes et al., 2009). Moreover, GAs have been used to solve multimodal, non-differentiable, discontinuous, or even NP-complete problems with very few mathematic requirements (Man et al., 1996). Many research works have been found in using GAs to solve optimization problems dealing with the discrete variables (Shafiei et al., 2004; He and Hui, 2006; Jezowski et al., 2007).

For continuous dynamic optimization (DO) part, a number of different techniques, including both stochastic and deterministic methods, have been proposed in the literature to solve the DO problem. A review of deterministic, stochastic and hybridization methods to solve DO can be found in Cervantes and Biegler (2000), Esposito and Floudas (200), and Banga et al. (2005). In particular, we are interested in a widely used class of deterministic methods that transform an infinite dimensional optimization problem into a finite-dimensional nonlinear programming (NLP) by discretization of control variables (optimization parameter). This method is known as control vector parameterization (CVP) or partial discretization method which the control or varying-time decision variables are discretized to transform infinite DO problem to finite-dimensional NLP problem. Note that there is also another well-known method which is in variable discretization class. This method is called complete discretization (CP) method as it completely discretizes the variable spaces both control and state variables in DO problem in order to transform the problem to the finite-dimensional NLP one. However, this technique is not considered in this work because the resulting NLP problem from discretization generates large number of variables and constraints (Bloss et al., 1999; Balsa-Canto et al., 2005). The solutions will be available only when the optimization is converged. Moreover, in CP method, the type of discretization used for the state profiles can have a dramatic effect on the solution due to the error introduced in the approximation (Esposito and Floudas, 2000). For these reasons, the CVP approach, which generate much smaller scale of NLP as well as existing integration routines can be employed to solve dynamic models, will be considered to solve the DO problem in this work. In the following section, a more detail of proposed hybridization method will be provided.

4.3 Hybrid Approach

As stated in previous sections, the hybridization method between stochastic (GA) and deterministic (CVP) method is proposed in this work to solve multistage MIDO arising from the synthesis problem of rice drying process involving system of differential algebraic equations (DAEs). The basic idea of a GA is to start from initially generated set of random solutions called population from the solution space. Each candidate solution in the population called chromosome will undergo the evolutionary mechanism of GA through selection, crossover and mutation process to explore and exploit the existing solution in a current generation in hope that the better one will be generated in a next generation. A review of GAs, their implementation issues and limitations can be found in Gen and Cheng (2000) and Younes et al. (2009).

For a CVP approach, it is a deterministic optimization method widely used for solving optimization problems involving systems of differential equations or transient processes. The basic idea of the CVP method is to transform an infinite-dimensional optimization problem into finite-dimensional NLP through approximation of control profiles by piecewise polynomial elements varying from simple piecewise constant to complicated polynomial one. Then, the properties of these elements become the decision variables of optimization problem (NLP). Using CVP approach, two subproblems are generated. One is master (outer) NLP and another one is (inner) initial value problem (IVP). The IVP is decoupled from the optimization stage and is integrated using existing DAE solvers in order to evaluate the objective function and the constraints. Then, the outer NLP, which is in the term of parameters defining the piecewise elements, is solved using well-known NLP techniques. In each iteration, the NLP algorithm adjusts the control parameters on the basis of gradient information obtained from sensitivity equations of objective function and constraints. This approach is also sometimes called sequential direct strategy (Banga et al., 2005). Nevertheless, note that from using CVP approach, since each function evaluation of performance index requires the intermediate solution of DAE system, the computational time can be very expensive sometimes (Balsa-Canto et al., 2005).

Taking the advantage of the population to population based approach of GAs to perform an efficient global search of a high dimensional discrete space generated by choice of configurations and at the same time the simplicity of transforming dynamic optimization problem into an NLP problem by CVP approach, the algorithm structure for the proposed hybrid method is presented in Figure 4.3. The hybrid algorithm starts by setting the GA parameters and randomly creating the initial population of chromosomes (candidate solutions). A chromosome consists of discrete variables that represent a possible configuration. Each chromosome is then evaluated by computing its fitness (objective function) using a CVP approach. In this evaluation step, MIDO problem is reduced to dynamic optimization (DO) since the discrete variables are fixed within each chromosome produced by the GA. The resulting DO problem can thus be solved with CVP approach using available NLP and differential equation solver. After the fitness is computed for each chromosome in the current population, the next step of the GA is to save a copy of the best solution (elitist strategy) as one of a chromosome in a population of next generation. Next binary tournament selection is performed with a probability (P_t) to retain some of chromosomes in the population and let the remainder chromosomes die out. To ensure diversity of the population, any duplicate chromosome after selection will be deleted. Next, three GA operators which include two-point crossover with crossover rate (P_c), inversion mutation with mutation rate (P_{m1}) and uniform mutation with mutation rate (P_{m2}) are applied to generate offspring which will be added to the current population without replacement. Finally, the termination criteria will be checked if the number of generation reaches the maximum number (max_gen). If the number of current generation is less than the specified number, the previous GA procedure will be repeated starting from the evaluation step of newly generated offsprings, otherwise the algorithm will be stopped and the final configuration and its corresponding optimal operating conditions will be considered as the solution of the MIDO problem.

4.4 Implementation of Hybrid Algorithm

In this section, the issue related to the implementation of the proposed hybrid method to the synthesis problem will be provided. As mentioned before, the synthesis problem with theoretical model gives rise to optimization called MIDO problem which involve both type of decision variables: discrete and continuous. Discrete variables are used to model the selection of drying configuration. Continuous variables are used to model the states and operating variables or control profiles associated in the drying processes. The proposed algorithm will decomposed the MIDO problem into discrete and continuous parts. GA will be used to solve for a discrete part (integer programming) while CVP approach will be used for a continuous part (dynamic optimization).

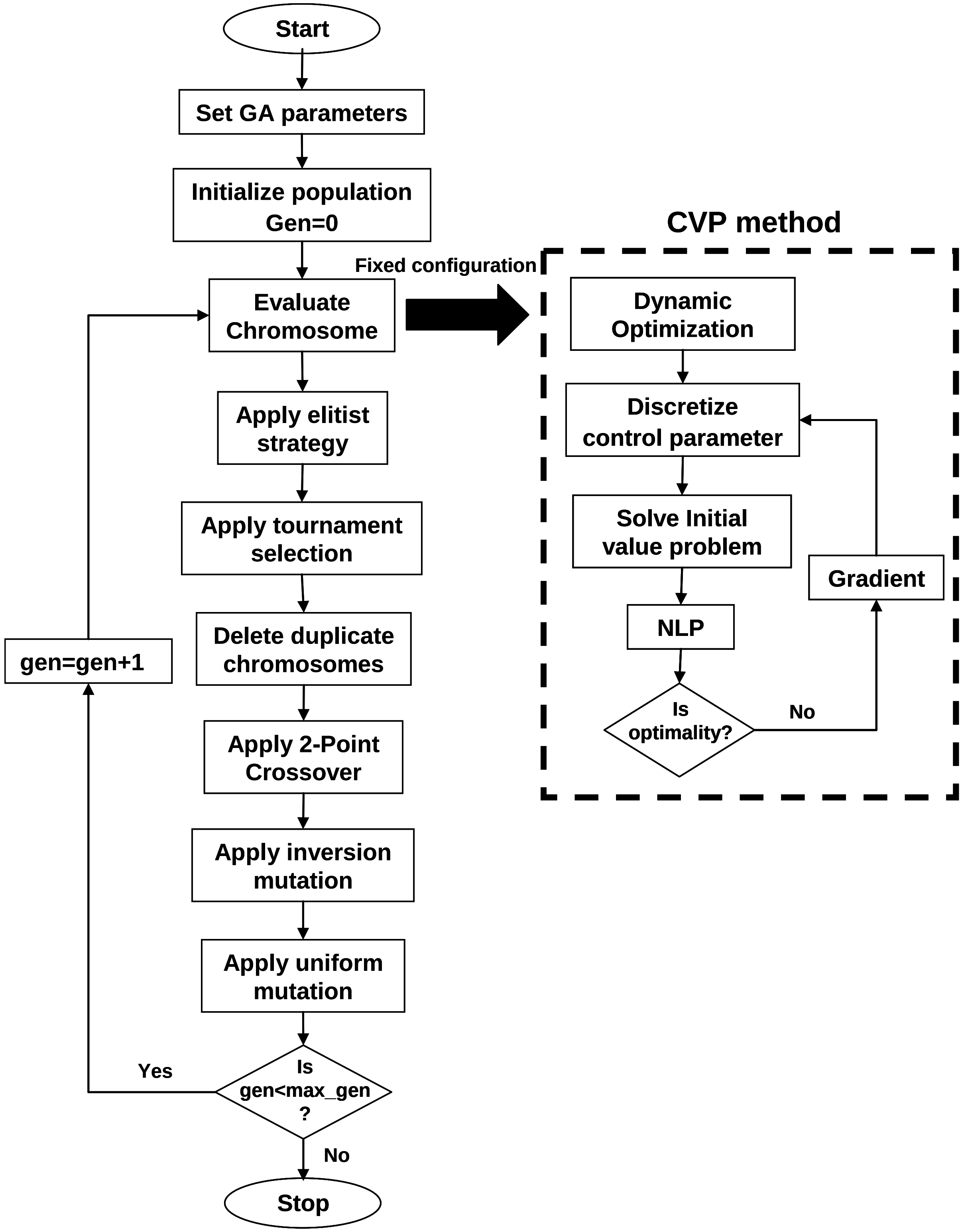


Figure 4.3. Algorithm structure of hybridization method.

4.4.1 Genetic algorithm

In this section, the explanation of how to use the proposed GA to deal with finding the optimal configuration is provided.

4.4.1.1 Chromosome representation

The important issue for GA implementation is to decide how the problem will be represented. In this work, a choice of configurations in each candidate chromosome will be represented by a string of integer numbers from the set of {0,1,2,3,4,5}. The meaning of each integer number corresponding to the choice of drying configurations is given in Table 4.3. The position of each gene in a chromosome corresponds to a pass number (j). Since the maximum number of passes allowed is 8; therefore, the maximum number of genes in one chromosome is 8.

Table 4.3. Choice of configurations corresponding to an integer number.

Inter number	Configuration
0	No units
1	drying-cooling
2	drying-tempering
3	cooling-tempering
4	drying-cooling-tempering
5	drying-tempering-cooling

An example of a chromosome representation is presented in Figure 4.4. In this chromosome, only 6 passes are required to dry rice from initial moisture content to the target moisture content. The drying configuration in the first pass is drying-cooling; the second pass is drying-tempering; the third pass is cooling-tempering; the fourth pass is drying-cooling-tempering; the fifth pass is drying-tempering-cooling; and finally the last pass is drying-tempering.

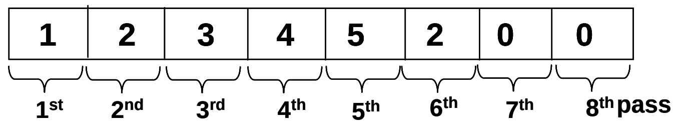


Figure 4.4. An example of a chromosome representation.

Note that each chromosome in a population is generated randomly; thus there is a possibility which an integer number “0” will be generated elsewhere (gene) in a chromosome. This means that there is no unit operations exist in the corresponding pass. However, from the physical insight, an integer number “0” should not be generated in any position of chromosome which is still followed by an integer number other than “0”. To prevent this situation to happen the procedure, which moves an generated integer number “0” to the position after the position of last integer number other than “0” found in a chromosome, will also be applied in this work to ensure the every generated chromosome is feasible.

4.4.1.2 Fitness function

The fitness function or evaluation function is used to evaluate and rank each chromosome in a population according to it fitness. The fitness function considered here is the value of objective function itself. There are two objective functions considered in this chapter; therefore finding the fitness values is to solve the DO problems as shown in Equations (4.13) to (4.17) and Equations (4.18) to (4.22).

In the evaluation process, due to the time consuming process in solving DO problem and also a huge number of total possible configurations, to ensure that the proposed method entirely search solution space as much as possible and save the computational time, our proposed GA also stored visited solutions of configurations in a list to prevent the revaluation process of already visited solution. Prior to evaluating a new chromosome, the choice of configurations represented by the chromosome will be checked against the list.

4.4.1.3 Selection

Selection is the process that determines which individuals in the current population will survive and reproduce offsprings. The general idea is that the chromosome which provides a better fitness value should have a better chance of surviving to the subsequent generation. In this work, elitist method combined with tournament selection is used in selection process. Elitist strategy will be used to preserves the best chromosome in the current population to next population (elitist_size =1). Tournament selection is a popular selection approach which randomly chooses a set of chromosomes (tournament_size) from a population and picks out the best chromosome or applies some degree of randomness (tournament probability, P_t) during selection for reproduction. This process continues until the desired number of chromosomes to be injected in the new population is reached. The tournament procedure applied in this work is as follows:

```
begin
    Setting elitist_size =1, tournament_size = 2, tournament probability =Pt
    repeat
        i= elitist_size+1;
        randomly select two chromosomes from the current population
        generate random number r
        if  (r<Pt) and (fitness(chromosome1) > fitness(chromosome2))
        then child(i)= chromosome1
        else  child(i)= chromosome2
        end
    until i=pop_size
end
```

4.4.1.4 Crossover

Crossover is used to recombine genetic material in parent chromosomes (usually two) to produce one or two child chromosomes that share characteristics of both parents using a crossover rate (P_C). The crossover rate is defined as a number of chances for chromosomes in a population which will undergo crossover operation. In this work two-point crossover is employed as depicted in Figure 4.5.

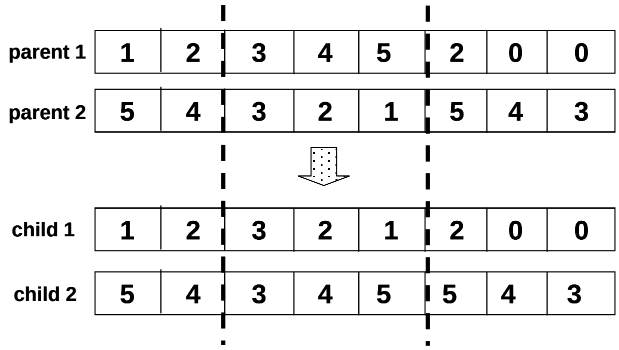


Figure 4.5. Two-point crossover.

From Figure 4.5, two cut points of strings in a chromosome are selected randomly, and then the portion of strings which are in between these two cut points in a parent chromosome are swapped to generate two new offsprings. The two-point procedure applied in this work is as follows:

begin

Setting crossover probability = P_C; i = 0; j=0;

generate random number r(i); i = 1, 2, …, pop_size;

repeat

  i = i +1;

  if r(i) < P_C;

  j = j +1;

  then chromosome(i) is selected to be parent(j);

  end

until i = pop_size;

if j is odd number

then remove the last selected chromosome from a set of parent chromosomes

end

select a pair of parent chromosomes to perform two-point crossover operation till all the parents in a set j (j= 1, 2, …,J) are undergone the operation;

end

4.4.1.5 Mutation

Mutation is used to introduce the new genetic material with mutation probability (P_m) into a population to maintain the diversity. Mutation plays a complementary role to the crossover, which works on material already present in the population and thus cannot introduce new genetic material (Younes et al., 2009). In this work two types of mutation techniques are employed: inversion mutation with mutation rate (P_{m1}) and uniform mutation with mutation rate (P_{m2}). With the inversion mutation, two positions within a chromosome are selected at random, and then the substring between these two positions is inverted as illustrated in Figure 4.6 and the inversion mutation procedure is shown below:

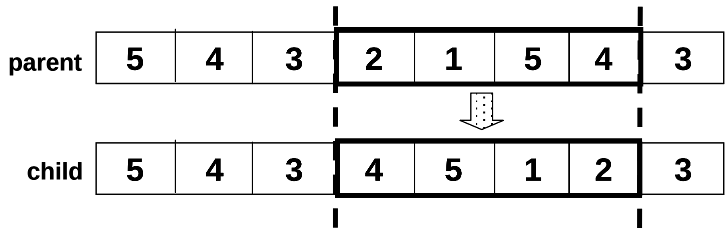


Figure 4.6. Inversion mutation.

begin

Setting inversion probability = P_{m1}; i = 0;

generate random number r(i); i = 1, 2, …, pop_size;

repeat

    i = i +1;

    if r(i) < P_{m1};

    then chromosome(i) is selected to be a parent for mutation;

    randomly select two points in strings of chromosome and perform inversion mutation;

    end

until i = pop_size;

end

For a uniform mutation, every gene of the chromosomes in the population has the same probability to undergo the mutation process. In this work, each chromosome contains 8 genes and population size (pop_size) equals to 10 is employed. Therefore 80 (8x10) random numbers are generated to assign to every gene in a population. A gene which has generated random number less than P_{m2} will be introduced a new integer number (choice of configurations) from a set {0,1,2,3,4,5}. Note that if new chromosome undergone this process introduces integer "0" in between other integer numbers in strings, the same procedure to remove "0" to the back of strings as applied in initialization step will be used. The procedure for uniform mutation is summarized as below:

begin
Setting inversion probability = P_{m2}; i = 0;
n = pop_size x maximum number of genes in a chromosome
generate random number r(i); i = 1, 2, …, n;
repeat
    i = i +1;
    if r(i) < P_{m2};
    then gene(i) in a population will be introduced a new integer number from a set
    {0,1,2,3,4,5};
    end
until i = n;
end

4.4.2 Control vector parameterization approach

As stated before, our proposed approach uses control vector parameterization (CVP) to solve the DO part of MIDO problem after the discrete variables obtained from GA are fixed. In CVP approach, to transform the continuous time problem into a final set of discrete points in time, varying time parameters (control variables) of optimization problems will be discretized with piecewise polynomial function. In our synthesis problem, those optimization parameters are the operating conditions (i.e. air temperature and relative humidity) or air conditions utilized in a dying and/or a cooling unit.

As we assumed earlier for the synthesis problem using the theoretical model, rice grains are supplied with the same quality of air in any position and throughout the time interval spent in any unit operation. Also, for the sake of simplicity; therefore constant piecewise control profiles are considered to be employed in this work. The idea is that over the time horizon required to dry rice from initial moisture content to the final moisture content, continuous time of operating parameters of air, which is temperature and relative humidity, will be discretized into subintervals. Each subinterval is relevant to the time spent in any unit operation existing in a drying system. Each operating condition in a subinterval will be at assumed constant. Thus, in one drying system, a total number of subinterval needed to be discretized is equal to a total number of unit operations existing in a drying system to dry rice from initial moisture content to the final moisture content. For example, a drying system has two passes which present "cooling-tempering" configuration in the first pass and "drying-cooling-tempering configuration" in the second pass. A total number of unit operations employed in this drying system equal to 5, therefore 5 subintervals will be generated over the time horizon.

After discretization, our continuous time dynamic optimization (DO) problem which are in the continuous space of operating conditions will be converted to finite NLP problem which are in a parameter space of operating value employed in each sub-time interval and the duration of that intervals. In conclusion, using the CVP to solve our DO problem with piecewise constant control profiles, the optimization parameters used to define the property of a piecewise control profile and needed to be found in each unit operation for NLP problem are summarized as follows:

- In a drying unit, operating temperature and relative humidity of drying air as well as a drying time,

- In a cooling unit, operating temperature and relative humidity of cooling air as well as a cooling time,

- In a tempering unit, a tempering time.

Note that in a tempering unit, we assume that there is no heat and mass transfer between air and grain phase. Only mass transfer between two the compartments is considered. Thus, there is no control of operating conditions in a tempering unit. Only the duration of time that rice needs to be rested in this unit must be found.

4.5 Case Study

The study of synthesis problems with theoretical models will be illustrated in this work with three case studies. In the first case study, the objective is to find the proper set of GA parameters which are robust and efficient for an implementation of our proposed method to solve the synthesis problem. In the second case study, we implement the proposed method to solve the synthesis problem with the quality objective function. This case study aims to maximize the grain quality (Q) at the end of drying process subjected to a set of DAEs system arising from theoretical model, final time constraints (target moisture) and bounds on control variables as shown in Equations (4.13) to (4.17). In the last case study, we solved the synthesis problem with energy objective function which aims to minimize the energy function subjected to the same set of constraints as employed in the maximizing quality problem shown in Equations (4.18) to (4.22).

Throughout this study, the solving DAE system arising from the compartmental model involves the solutions of the state variables which are the moisture content in the inner compartment (x_1, %d.b.), the moisture content in the outer compartment (x_2, %d.b.) and the grain temperature (T_g, ^{o}C) as well as the grain quality (Q, %decimal). The initial conditions of the state variables are given in Table 4.4.

Table 4.4. Initial conditions of state variables of rice grain.

State variables	Value
$x_1(0)$	34% d.b.
$x_2(0)$	34% d.b.
$T_g(0)$	20^{o}C
$Q(0)$	70%

In every case study, the solutions of the synthesis problem needed to be found are summarized below:

- Total number of passes (J) required for drying rice from initial moisture content (M_i) to final moisture content (M_f).

- The configuration of unit operation in each pass (j), whether it consists of a drying unit (D_j), a cooling unit (C_j), a tempering unit (P_j), or a combination of them.

- Operating conditions of unit operations which exist in the flowsheet in each pass. For a drying unit, they are drying air temperature ($T_{D\,j}$), relative humidity of drying air (RH_{Dj}) and drying time (t_{Dj}); a cooling unit, they are cooling air temperature ($T_{C\,j}$), relative humidity of cooling air ($RH_{C\,j}$) and cooling time ($t_{C\,j}$); and finally for a tempering unit, it is tempering time ($t_{P\,j}$).

The bounds on the operating condition applied to the problem are given in Table 4.5.

Table 4.5. Bound of operating conditions employed in the compartmental model.

Variable	Lower bound	Upper bound
TD_j (^oC)	35	80
RHD (%)	5	80
TC_j (^oC)	20	30
RHC_j (%)	5	80
tD_j (hrs)	0	2
tC_j (hrs)	0	4
tC_j (hrs)	0	6

To solve the synthesis problem, the computer code for proposed hybrid method is developed and implemented in MATLAB 2006b and run on AMD Athlon 3.21 GHz under Windows operating system. Function “fmincon” in MATLAB is used to solve NLP problem after transformation of dynamic optimization (DO) with CVP approach and function “ode15s” is employed to solve stiff dynamic models of rice grain.

4.5.1 Tuning GA parameters

Like any other stochastic methods, tuning GA parameters is one important key element for successful implementation of GA. Parameter tuning directly plays an important role in balancing exploration and exploitation during the search process to maintain population diversity. Increasing diversity drives GA to search for unvisited regions of search space while decreasing diversity drives GA to focus the search on specific promising region (Younes et al., 2009). In other word, tuning becomes mandatory in order to obtain a good compromise between robustness and efficiency (Balsa-Canto et al., 2005).

Deciding on the best set of parameter value is not a trivial tasks and the issue still remains open to suggestion even some guidelines have been introduced (Man et al., 1996). From our proposed method, the GA parameters are population size (pop_size), maximum number of generations (max_gen), crossover rate (P_c), inversion mutation rate (P_{m1}), uniform mutation rate (P_{m2}) and tournament selection rate (P_t). However, the choice of population size and maximum number of generations mainly affect the calculation time. Therefore, in this work, deciding on the value of these parameters will be mainly based on the time constraint. From a preliminary test, the population size equal to 10 and maximum number of generation equal to 300 will be set for GA throughout this study unless stated otherwise.

Aside from those two parameters, eleven sets of GA parameters were tested to find the proper set of GA parameters which can provide a good trade-off between exploration and exploitation of population diversity and the results are shown in Table 4.6. Note that in this study the synthesis problem with objective function of maximizing the quality of rice grain was used for tuning GA parameters. The first column in this table represents the number of parameter set, the second column represents values of GA parameters, the third column represents the number of runs, the fourth column represents the optimal configuration, the fifth column represents the optimal value of quality, the sixth column represents the number of solved dynamic optimization problems, and the final column represents the total CPU time required for 300 generations.

Each parameter set was run two times and from the results we found that all the runs of different parameter sets converge to different configurations and different total number of passes; however, the values of the objective function at the end of 300 generation are close to each other (the quality value of each parameter set is different with a significance of 10^{-3}). This means that the choice of configuration (discrete part) of drying system has minimal effect on quality of rice grain. The optimization parameters which have the main effect on the quality of rice grain are operating conditions (continuous part). Finding the optimum operating condition directly involves the solution of a dynamic optimization (DO) problem.

Table 4.6. Optimal solutions of the synthesis problem from using different GA parameter sets.

Set	GA Parameters				Run	Configuration	Q(%)	# of evaluations	CPU (hrs)
	Pc	Pm1	Pm2	Pt					
1	0.00	0.10	0.01	0.75	1	5 3 3 3 3 2 0 0	69.9965	1341	15.48
					2	1 1 5 3 3 1 2 0	69.9917	1406	16.70
2	0.50	0.10	0.01	0.75	1	5 1 3 3 3 5 0 0	69.9986	2537	26.92
					2	3 3 5 5 3 4 3 5	69.9988	2559	28.87
3	0.60	0.10	0.01	0.75	1	4 4 1 3 3 3 3 2	69.9982	2797	30.50
					2	2 5 3 3 3 3 3 3	69.9982	2789	29.42
4	0.70	0.10	0.01	0.75	1	1 2 1 3 3 2 4 1	69.9983	3013	31.75
					2	3 2 1 5 3 3 3 0	69.9991	3084	30.35
5	1.00	0.10	0.01	0.75	1	2 3 4 2 4 4 2 0	69.9990	4041	44.08
					2	4 4 3 3 1 5 0 0	69.9993	3939	42.94
6	0.70	0.10	0.05	0.75	1	3 2 5 3 3 5 0 0	69.9980	4280	44.23
					2	5 2 5 3 3 4 2 0	69.9970	4293	51.50
7	0.70	0.00	0.01	0.75	1	1 2 3 2 2 5 3 5	69.9987	2554	26.54
					2	2 3 3 4 4 2 0 0	69.9962	2628	30.26
8	0.70	0.01	0.01	0.75	1	2 1 2 3 3 1 5 0	69.9989	2742	27.93
					2	2 1 5 3 1 5 2 0	69.9973	2648	30.27
9	0.70	0.10	0.01	0.60	1	2 1 5 3 3 2 0 0	69.9989	3070	33.61
					2	5 3 3 4 3 3 5 0	69.9993	2984	30.89
10	0.60	0.10	0.05	0.75	1	2 2 1 2 2 3 1 2	69.9985	3890	44.42
					2	5 4 3 5 3 3 3 0	69.9984	3989	40.63
11	0.60	0.10	0.05	0.60	1	4 5 1 3 3 2 2 2	69.9991	3893	46.16
					2	3 5 3 3 3 3 5 1	69.9993	3947	41.30

Also from using the proposed algorithm, we found that computational time of the algorithm is significantly dedicated to solve the DO problem. The more DO problems were generated per a population by a GA parameter set, the more computational time was spent on the convergence of the algorithm. This is because the function evaluation process (fitness function) involves numerical integration of highly nonlinear system of DAEs system arising from the theoretical model. Considering the quality model of Abud-Archila et al. (2000), the term which mainly contributes to quality degradation is moisture gradient between two compartments. As a result, finding the operating conditions which produce the least amount of moisture gradient within the rice grain is the key factor to maintain the quality of rice grain. In the following section, more detail of the search on the optimum solutions of the synthesis problem with quality objective function will be provided.

Since the values of objective function found from different GA parameter sets is not significantly different, to find the best set of GA parameters, two runs from each set of parameters are plotted and shown in Figure 4.7. From Figure 4.7, one run of parameter set 11 gives the highest quality and at the same time it is robust in the sense that it can find the comparable best objective values from both runs. For this reason, the GA parameters form set 11 (P_c=0.6, P_{m1}=0.10, P_{m2}=0.05 and P_t=0.6) will be considered as GA parameters to be used throughout this study. It should be noted that the stochastic nature of GA might produce different values of quality with more runs. Unfortunately, function evaluation of dynamic part is a time-consuming process that prohibits repeating the experiments. One of our future works will be to increase the number of runs per settings.

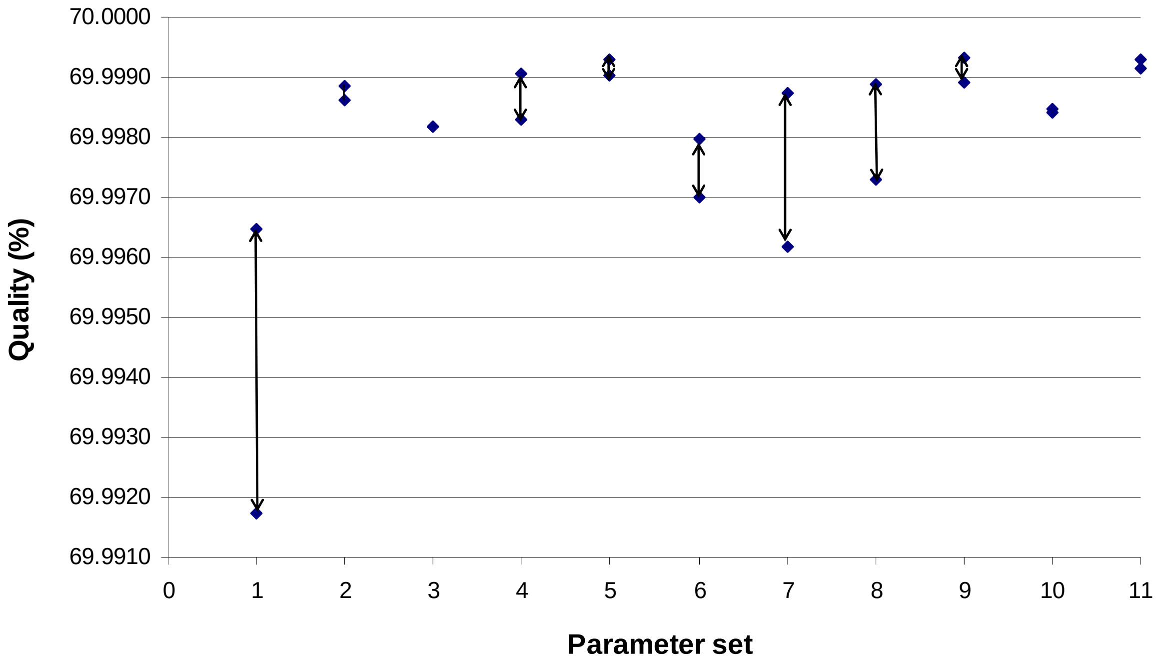


Figure 4.7. Comparison of objective function value from 2 runs of each parameter set.

4.5.2 Maximization of head rice yield

Due to the stochastic nature of GA, the proposed algorithm is run 10 times on the synthesis problem with quality objective function using the parameter set of GA found in previous section. The convergence of proposed algorithm for 10 runs is presented in Table 4.7 and Figure 4.8.

From Table 4.7, all the runs converge to different objective values at the significance of 10^{-3}; however, the seventh run gives the highest quality (69.9993%) with the configuration of "5 3 5 4 3 3 4 0". This means that seven passes are required to dry rice from initial moisture content (35% d.b.) to the target moisture content (14% d.b.). The first pass of configuration is drying-tempering-cooling followed by the second pass which is cooling-tempering, the third pass is drying-tempering-cooling, the fourth pass is drying-cooling-tempering, the fifth pass is cooling-tempering, the sixth pass is cooling-tempering, and the final pass is drying-cooling-tempering.

Table 4.7. Best configuration and quality found from 10 runs of synthesis problem with quality objective function.

Run	Best configuration	Best quality (%)
1	3 4 3 4 3 3 2 0	69.99891
2	3 5 3 3 3 3 2 0	69.99925
3	5 5 3 5 3 5 0 0	69.99917
4	3 2 3 4 3 1 5 0	69.99878
5	2 2 3 4 4 4 2 5	69.99921
6	1 5 3 2 1 2 2 0	69.99897
7	5 3 5 4 3 3 4 0	69.99932
8	3 3 2 2 2 5 2 2	69.99884
9	4 5 1 3 3 2 2 2	69.99914
10	3 5 3 3 3 3 5 1	69.99929

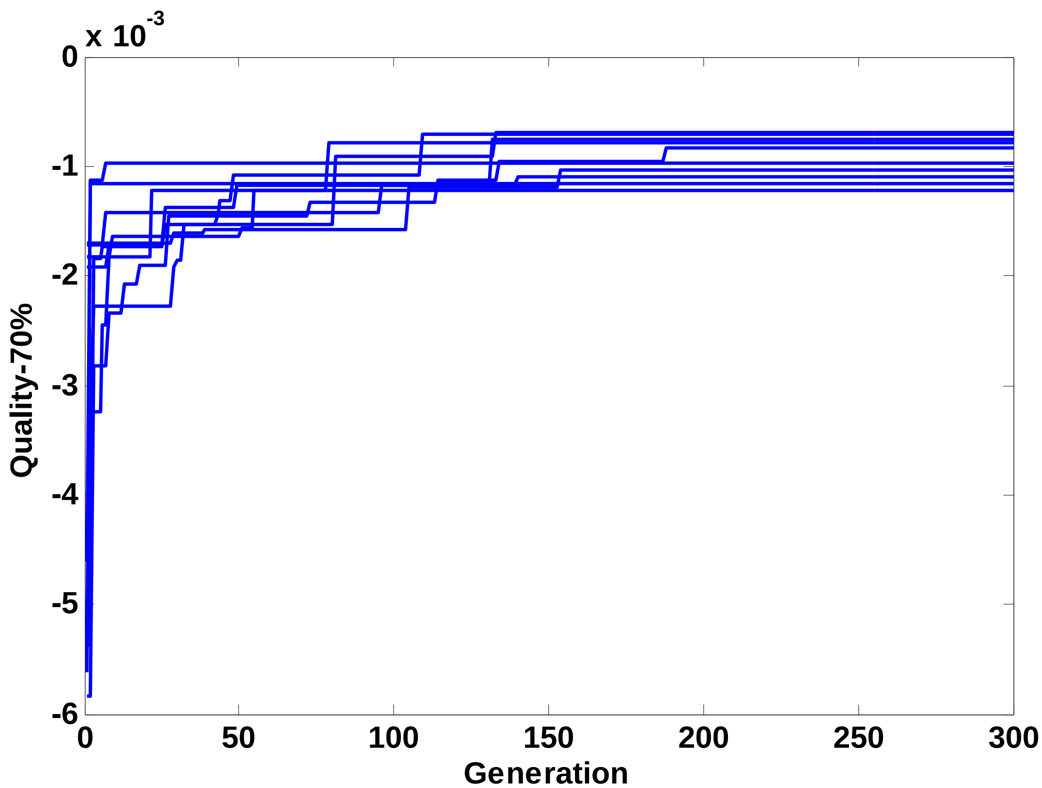


Figure 4.8. Convergence of quality with the number of generations.

Also from Figure 4.8, we observed that 3 out of 10 runs converge to very close objective value with configuration of "3 5 3 3 3 3 2 0", "5 3 5 4 3 3 4 0", and "3 5 3 3 3 3 5 1", respectively. Although, this three runs give different configurations and total number of passes, the best configurations found from this three runs tend to converge to the configurations which include a tempering unit in each pass. This finding is supported with the reason that having a tempering unit in a drying system will serve to equalize the moisture gradient developed during the drying process and the quality of rice grain will be preserved (Steffe and Singh, 1980).

Since we found from previous study and in this case study that a choice of configurations (discrete part of MIDO problem) does not have a significant effect on the quality of rice grain while the operating conditions (continuous part of MIDO problem) do, therefore the highly-nonlinear dynamic optimization with 1000 randomly generated initial guesses will be solved with best configuration found ("5 3 5 4 3 3 4 0").

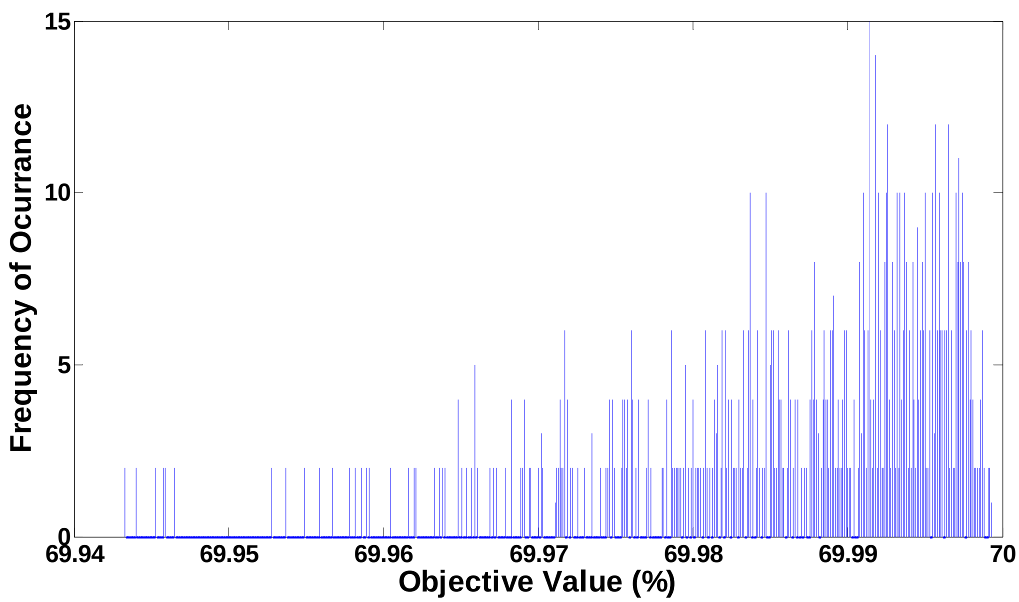


Figure 4.9. Frequency plot of local solutions found using 1000 starting points for synthesis problem with quality objective function and fixed configuration "5 3 5 4 3 3 4 0".

Figure 4.9 is a frequency plot of local solution found from solving the synthesis problem with quality objective function using 1000 random starting points and the result show that 813 local solutions have been found. Also each of the local solution has a completely different control profiles. This finding proves that the dynamic optimization considered here is highly nonlinear and multimodal. However, solving the synthesis problem to the global optimality is not a focus in this work due to the reason that the quality of best local solution found is acceptable in the sense that almost the original quality of rice grain can be preserved. Chachuat et al. (2005) also stated that solving the MIDO problem to global optimality typically represents the majority of the overall computational time. This requirement is weakened if only feasible point is provided. The best control profiles of temperature and relative humidity of air which give the highest quality (69.9993%) are shown in Figure 4.10.

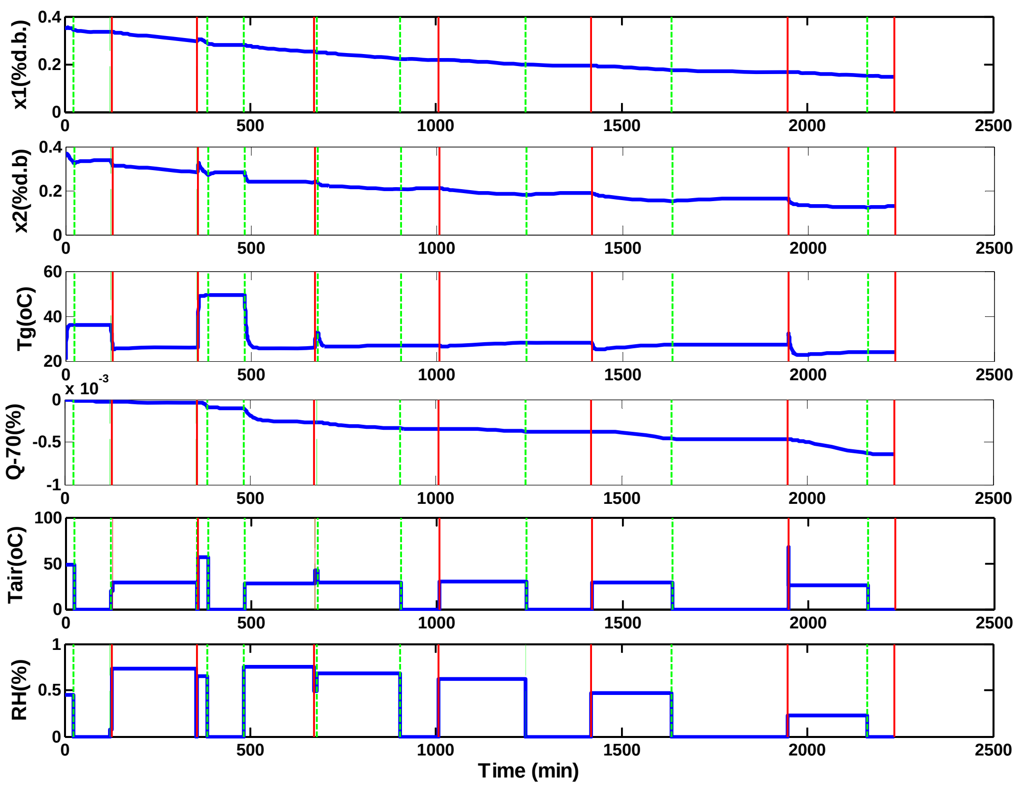


Figure 4.10 The state and control profiles of the best quality found from configuration“5 3 5 4 3 3 4 0”.

In Figure 4.10, vertical solid line represents the switching of state and control profiles to the new pass and vertical dash line represents the changing of state and control profiles to a different unit operation within the same pass. For example, the first pass which is the configuration of drying-tempering-cooling, we show two vertical dash lines within the area of the first vertical solid line which means that there is a changing of a unit operation from a drying unit to a tempering unit and then a cooling unit in the first pass. Note that there is no control of temperature and relative humidity in a tempering unit; hence, control profile of temperature and relative humidity in a tempering unit is shown as zero value.

Also, to illustrate how the moisture of quality of rice grain can be preserved, the plots between the moisture content of both compartments (x_1 and x_2) and the quality are shown in Figure 4.11. Clearly, when there is more moisture gradient between two compartments developed, the steeper line of quality degradation is observed. The gradient of moisture content between two compartments is equilibrated when a tempering unit exists in each pass.

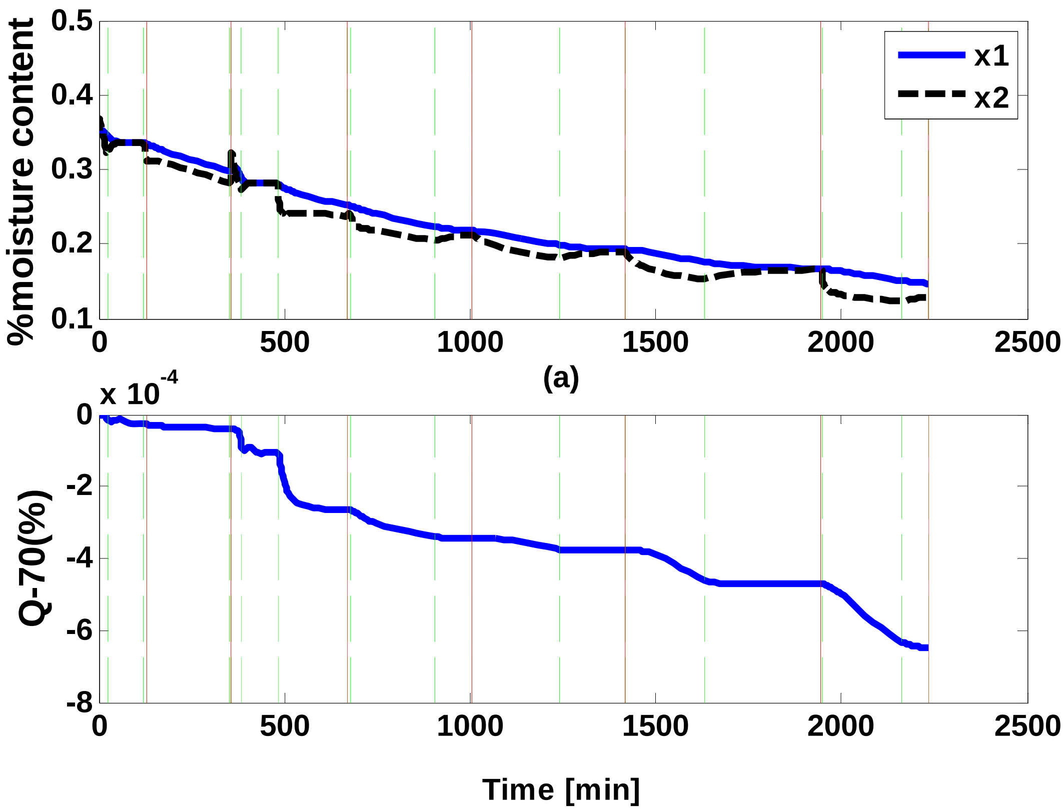


Figure 4.11. The state profiles of moisture contents and quality of rice grain from the best solution found from configuration“5 3 5 4 3 3 4 0”.

The optimum drying configuration, operating conditions, inlet and outlet moisture in each pass found in the synthesis problem with quality objective function are shown in Figure 4.12. The % average moisture reduction in each pass is 1.4, 3.4, 4.6, 3, 2.4, 2.5 and 2.7 respectively. As shown in Figure 4.11, a steep decrease of quality profile in a last pass is due to high moisture gradient developed during the drying process. Here in Figure 4.12 also showed that high moisture gradient developed is related to the high drying temperature (68^0C) and low relative humidity (5%) was used.

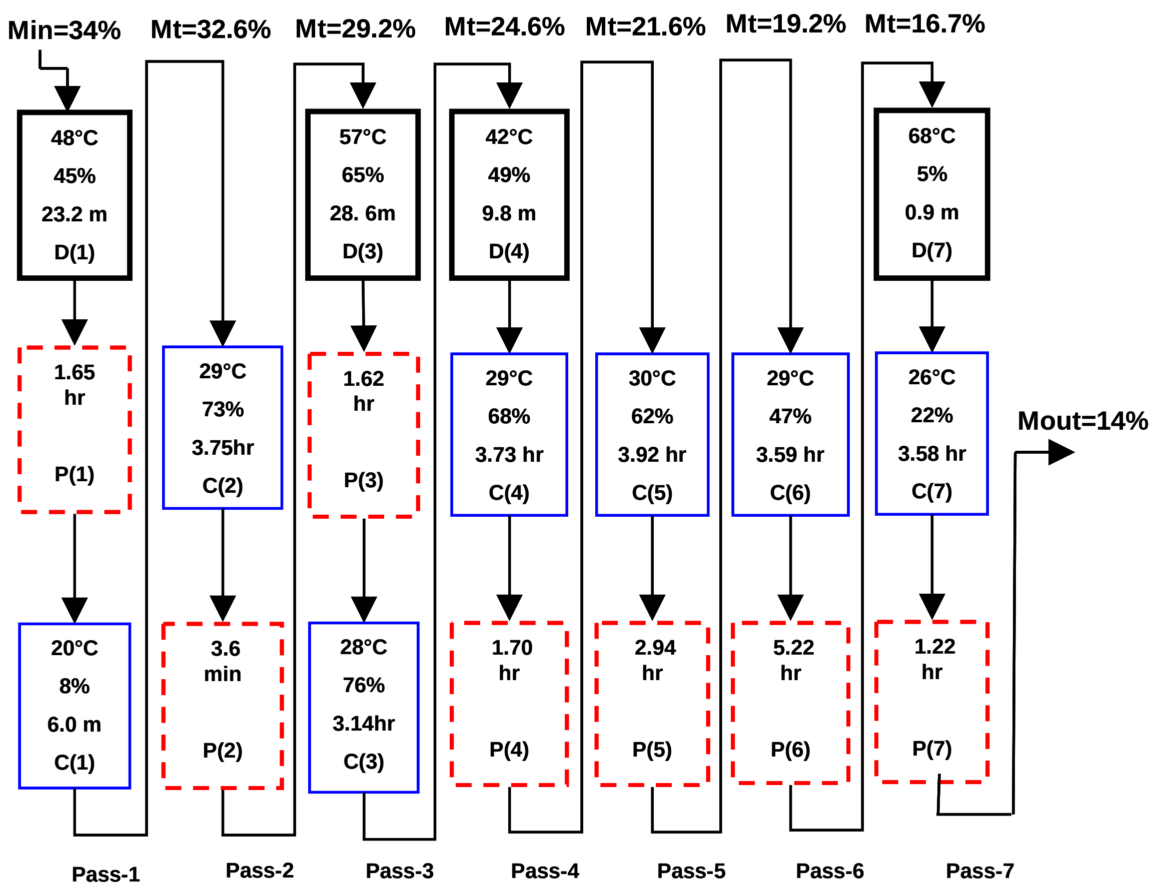


Figure 4.12. Optimum configuration of the synthesis problem with quality objective function using the theoretical model.

4.5.3 Minimization of energy consumption

For the use of proposed hybrid method in solving the synthesis problem to minimize the energy function, the same set of GA parameters as applied in previous case study was used except for the maximum number of generations. From some preliminary runs we found that a maximum number of generation equals 100 is enough for the convergence of energy problem. This is probably due to the fact that energy function (as shown in Equation 4.12) is simple-integral linear function of air temperature. Therefore, parameter "max_gen" of GA equals to 100 will be used in this case study. The results of running the proposed algorithm 5 times to solve the energy problem are given in Table 4.8.

Table 4.8 Best configuration and energy found from 5 runs with 4 hrs maximum operating time allowed in a cooling unit from 100 generations.

Run	Optimal configuration	Optimal Energy	Quality (%)	# of Function evaluations	CPU (hrs)
1	3 3 3 3 3 0 0 0	0	69.9959	1331	54.50
2	3 3 3 3 3 0 0 0	0	69.9963	1390	63.12
3	3 3 3 3 3 3 3 0	0	69.9957	1375	70.69
4	3 3 3 3 3 3 0 0	0	69.9966	1473	70.22
5	3 3 3 3 3 0 0 0	0	69.9952	1325	57.92

From Table 4.8, we found that although the synthesis problem with the energy objective function was solved for only 100 generation and the objective function is a simply linear function of air temperature, the calculation time used is longer than the quality objective function problem. This is probably due to the reason that NLP solver in MATLAB can solve the energy problem to the optimal solution which satisfies the optimality condition while in the quality problem, the NLP solver will terminate when some conditions was reached (only feasible solution). For example, change in the objective function value is less than some tolerance. This is from the fact that the quality objective function is highly nonlinear.

In every run, the same value of objective function (E=0) and the same choice of configurations were found. However, the total number of passes required is different. Also, different state and control profiles are obtained as shown in Figure 4.13. For a choice of configuration, alternative 3 which is cooling-tempering configuration was obtained. The reason of having a cooling unit is that range of operating conditions of this unit is allowed to operate at ambient temperature. Therefore, there is no need for an energy source to heat up the air. For a tempering unit, the purpose of this unit is to equalize the moisture gradient developed during the drying processes.

From Figure 4.13, this again showed that the dynamic problem part is multimodal. There are more than one set of operating conditions which can be operated to dry rice from initial moisture content to the desired final moisture content while minimize the energy function. From Figure 4.13, the shortest drying time (Run number 5) gives the lowest quality; however the longest drying time (Run number 3) does not give the highest quality. In the other hand, run number 4 gives the highest quality (Q=69.9966%). From this result, we conclude that with a same configuration in each pass the quality of rice grain does not depend on one or two factors alone. It was affected by the combine effect of operating conditions from start to the end of drying processes. This conclusion is the same as we found in case study of the synthesis problem with quality objective function.

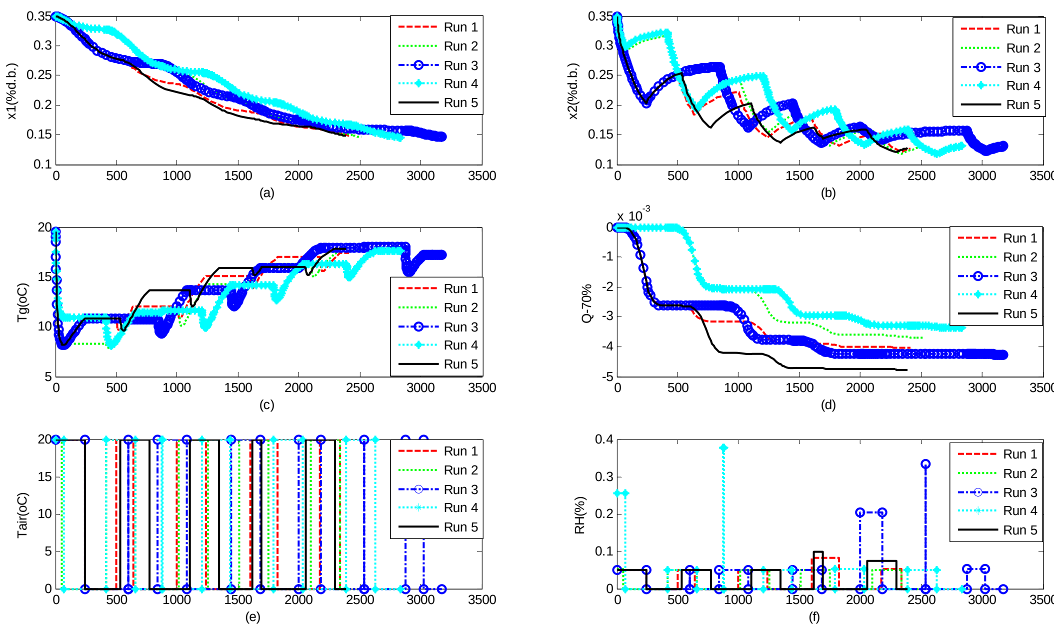


Figure 4.13. State and control profiles obtained from solving the synthesis problem with energy objective function from five runs.

The optimum drying configuration, operating conditions, inlet and outlet moisture in each pass found in the synthesis problem with energy objective function are shown in Figure 4.14. The % average moisture reduction in each pass is 1.5, 7.5, 0, 5.3, 3.6, and 2.4 respectively. As we saw in Figure 4.14, the reason that value of objective function is equals to zero (E=0) because every cooling unit is operated at ambient temperature (we assumed here that an ambient temperature is equal to 20^{o}C). We also observed that most of the operating time in cooling units is at the upper bound of operating time allowed in a cooling unit (4 hours) and the results from five runs converge to the same configuration with different total number of passes. The maximum number of passes required is 7 and the minimum number of passes required is 5. Therefore, the effect of the upper bound of cooling time allowed on the total number of passes required for drying rice will be studied.

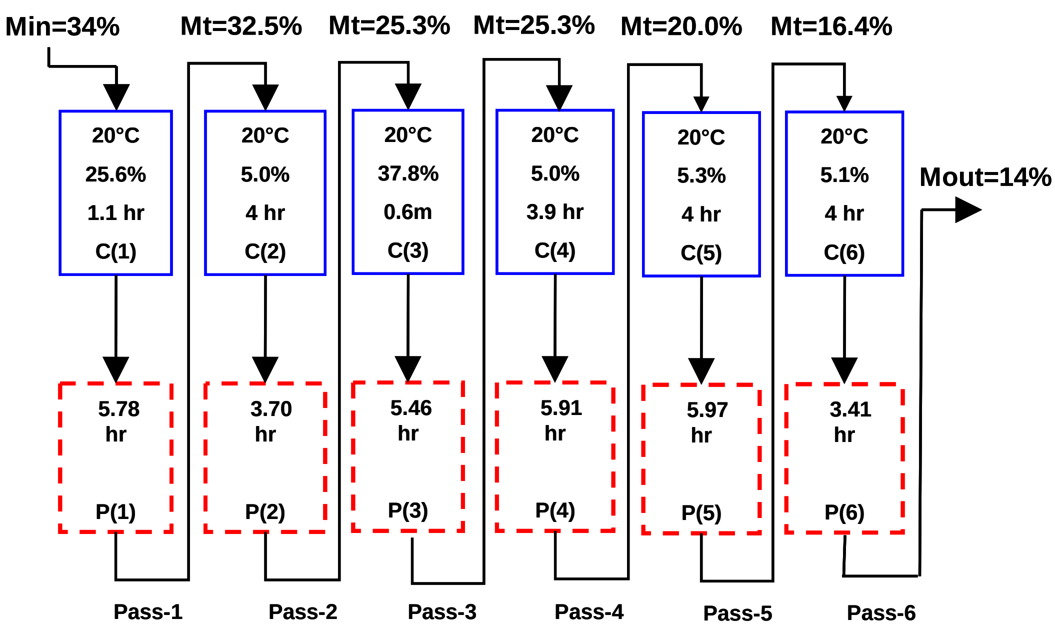


Figure 4.14. Optimum configuration of the synthesis problem with energy objective function using the theoretical model with 4 hr maximum cooling time allowed.

A set of maximum cooling time used for study their effects is 6, 8 and 12 hr. The results are shown in Table 4.9 to 4.11.

Table 4.9. Best configuration and energy found from 5 runs with 6 hrs maximum operating time allowed in a cooling unit from 100 generations.

Run	Optimal configuration	Optimal Energy	Quality (%)	# of Function evaluations	CPU (hrs)
1	3 3 3 3 0 0 0 0	0	69.9917	1354	64.52
2	3 3 3 3 0 0 0 0	0	69.9917	1384	61.88
3	3 3 3 3 0 0 0 0	0	69.9945	1330	65.94
4	3 3 3 3 3 3 0 0	0	69.9922	1372	70.41
5	3 3 3 3 0 0 0 0	0	69.9941	1321	57.55

Table 4.10. Best configuration and energy found from 5 runs with 8 hrs maximum operating time allowed in a cooling unit from 100 generations.

Run	Optimal configuration	Optimal Energy	Quality (%)	# of Function evaluations	CPU (hrs)
1	3 3 3 3 0 0 0 0	0	69.9915	1342	59.00
2	3 3 3 3 0 0 0 0	0	69.9903	1318	60.10
3	3 3 3 3 3 3 0 0	0	69.9940	1401	65.47
4	3 3 3 3 0 0 0 0	0	69.9897	1456	64.35
5	3 3 3 3 0 0 0 0	0	69.9900	1348	62.68

Table 4.11. Best configuration and energy found from 5 runs with 12 hrs maximum operating time allowed in a cooling unit from 100 generations.

Run	Optimal configuration	Optimal Energy	Quality (%)	# of Function evaluations	CPU (hrs)
1	3 3 3 3 3 0 0 0	0	69.9969	1375	96.50
2	3 3 3 3 3 3 3 3	0	69.9987	1407	86.31
3	3 3 3 0 0 0 0 0	0	69.9916	1444	81.20
4	3 3 3 3 3 3 0 0	0	69.9975	1392	74.25
5	3 3 3 3 3 0 0 0	0	69.9968	1465	83.55

From Table 4.9 to Table 4.11, every run of each maximum cooling time converges to the same configuration (cooling-tempering) at different total number of passes. The minimum and maximum number of passes required for each upper bound value of cooling time is summarized in Table 4.12.

Table 4.12. The minimum and maximum number of passes required for each upper bound value of cooling time.

	4 hrs	6 hrs	8 hrs	12 hrs
minimum number of passes	5	4	4	3
maximum number of passes	7	6	6	8

From Table 4.12, the results show that the upper bound of operating time allowed in a cooling unit affects the total number of passes required to dry rice from initial moisture content to the target moisture content. As expected, the maximum cooling time allowed (12 hrs) gives the lowest total number of passes (3 passes) required; however, also at 12 hr cooling time gives the solution of drying strategy which used the maximum number of passes (8 hrs). Therefore, this result show that not only the upper bound of cooling time allowed will affect the total number of passes required to dry rice but also other operating conditions (e.g. relative humidity of cooling air). Nevertheless, from the result we conclude that less number of passes would be obtained from allowing longer period of cooling time in a cooling unit. Moreover from an engineering view point, the more the number passes employed in a drying process, the more the usage of the energy should be required. Thus, the energy function considered as the function of only air temperature is too simply to take into account the other factors which contribute to the amount of energy used in a real drying system.

Comparing the rice quality obtained from all runs for the synthesis problem with energy objective function, run number 2 of 12 hrs maximum operating time allowed gives the highest quality (69.9987%). Therefore, the drying system which uses minimum energy consumption while maintains the quality of rice grain is represented in Figure 4.15. The % average moisture reduction in each pass is 4.8, 3.2, 2.9, 3.2, 2.3, 2.1, 1.4 and 0.1 respectively.

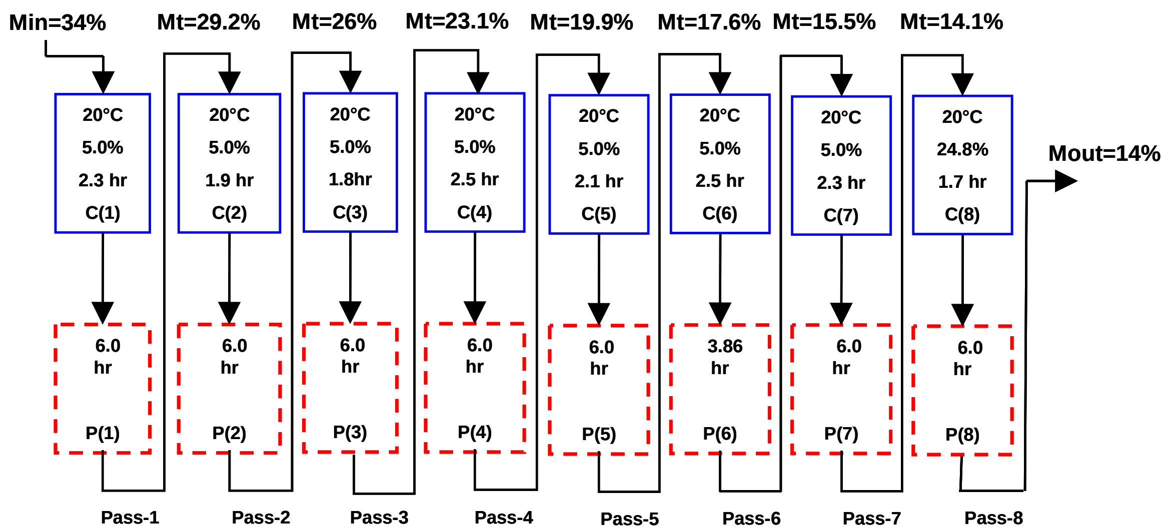


Figure 4.15. Optimum configuration of the synthesis problem using the theoretical models which minimize the energy objective function while maintains the quality of rice grain.

4.6 Conclusions

A thorough study of the synthesis problem of rice drying processes using the theoretical model has been investigated in this chapter. This synthesis problem is difficult to solve due to the reason that it deals with a set of different algebraic equations at a different stage in a drying process when there is a change of unit operation. This problem called mixed-integer dynamic optimization (MIDO) problem.

In this chapter the hybrid method combined GA and CVP approach was proposed to solve the synthesis problem. The application of the proposed method was illustrated with case studies. Two synthesis problems were considered here. One is the synthesis problem which aims to maximize the quality of rice grain. The results found from this problem showed that quality of rice grain can be preserved regardless to the choice of drying configurations. The combined effect of operating conditions throughout the drying process plays an important role to maintain the quality of rice grain. Moreover many drying strategies (drying configurations and operating conditions) have been found from using the proposed method to solve the synthesis problem.

Another synthesis problem aims to minimize the energy objective function. The results found from this problem showed that as long as a drying configuration in each pass is “cooling-tempering” and the operating temperature in a cooling unit is at the ambient temperature, the minimum energy objective function will be obtained. Nevertheless, we commented that the energy function employed here is too simply to take into account the other factors which contribute to the amount of energy used in a real drying system. Also, the effect of maximum cooling time allowed in a cooling unit in the solution of total number of passes required was studied. The results showed that less number of passes would be obtained if longer period of cooling time in a cooling unit is allowed.

Using the proposed method to solve the synthesis problem, the computational time is still expensive. This computational time is mainly contributed to solve dynamic optimization problem (continuous part of the MIDO problem) in every evaluation step of GA. In the future work, parallel computation might be considered to reduce the cost for solving the problem with proposed method.

Chapter 5
Conclusions and Recommendations

5.1 Conclusions

The synthesis problems of rice drying processes with various types of drying models both empirical and theoretical were thoroughly investigated. Each drying model applied in the synthesis problem was investigated under two objective functions: maximization of head rice yield and minimization of energy consumption. Mathematical programming was used as a tool to solve the synthesis problem for finding the optimal configuration and operating conditions of rice drying processes. Superstructure representation, problem formulation and solution strategy which are the basis components of mathematical programming approach were established here for each particular type of the synthesis problem arising from using different kinds of drying models.

5.1.1 Synthesis problem with empirical models

For the synthesis problem with empirical models, the various empirical models proposed in the form of widely used Page's model which are valid in a different range of drying operations were employed. Three alternative choices of rice drying configurations were embedded in the superstructure. They are drying-tempering, drying-cooling and drying-cooling-tempering. The logic-based modeling framework called GDP which has been accepted as an alternative to MINLP was utilized for deriving the MINLP models for this class of synthesis problems. Also the benefits of posing the synthesis problem from the GDP framework were studied here. The synthesis problems with empirical models were solved in GAMS.

Different empirical models gave rise to different drying strategies both optimal process configuration and operating conditions for the synthesis problem with maximizing quality objective function because of nonlinear characteristic of the objective function. On the contrary, due to the linear characteristic of the objective function, the same drying strategy both optimal process configuration and optimal operating conditions were obtained from solving the synthesis with minimizing the energy objective function.

The benefit of posing the synthesis problem with the GDP framework is that the MINLP model derived from the GDP model provides a better structure relationship of variables (discrete and continuous) represented in the problem formulation of the synthesis problems. Even though this GDP framework generated more variables and constraints to the problem formulation, the calculation time of MINLP derived from the GDP models is significantly less than the MINLP derived from the ad hoc basis. This characteristic found to be useful for the synthesis problem dealing with the nonlinear objective function such as in the case of maximum head rice yield but not in the case of minimum energy consumption (linear objective function).

Furthermore, the application of the GDP model to the synthesis problem facilitated the formulation of the problems to integrate the choices of drying models valid only in a small range of drying operations to extend the ability of the synthesis problem for the analysis of rice drying processes in the real application.

5.1.2 Synthesis problem with the theoretical models

For the synthesis problem with theoretical models, the proposed compartmental model from Abud-Archila et al (2000a) was employed. This model was derived from the principles of mass and energy balances by considering rice as two homogenous compartments. Five alternative choices of rice drying configurations were embedded in the superstructure. They are drying-cooling, drying-tempering, cooling-tempering, drying-cooling-tempering and drying-tempering-cooling. The synthesis problem using the theoretical model gave rise to a problem formulation called mixed-integer dynamic optimization (MIDO). The MIDO problems then were solved with a proposed hybrid method which combined a genetic algorithm (GA) and a control vector parameterization (CVP) approach. With the proposed algorithm, the MIDO problem was decomposed into an outer integer programming and inner dynamic optimization subproblem. GA was used to search for the discrete decision part (an optimum configuration) while the CVP approach was used to solve for the continuous part (dynamic optimization). The proposed algorithm was coded and implemented in MATLAB to solve the synthesis problem.

Prior to the implementation of the proposed algorithm, finding the appropriate choice of GA parameters for the synthesis problem was performed. From solving the synthesis problem with the quality objective function, the results showed that high quality of rice grain can be preserved regardless of the choice of drying configuration. The combined effect of operating conditions throughout the drying process plays an important role in maintaining the quality of rice grain. The key factor is that the drying process should be operated under the condition which produces the least amount of moisture gradient within the rice grain throughout the drying process. Due to the highly nonlinear nature of the dynamic models employed here, many local solutions (drying configuration and operating conditions) have been found.

For the synthesis problem with the energy objective function, the results showed that as long as a drying configuration in each pass is "cooling-tempering" and the operating temperature in a cooling unit is at the ambient temperature, the minimum energy objective function was obtained. Nevertheless, different operating conditions and the total number of passes were obtained at this configuration due to the nonlinear dynamic models employed in the problem. We found that the energy function employed for the synthesis problem is too simple to take into account the other factors which contribute to the amount of energy used in a real drying system. Cooling-tempering is the only optimal configuration found but different total number of passes and operating conditions were obtained for this configuration. Also, the effect of maximum cooling time allowed in a cooling unit on the solution of total number of passes required was studied. The results showed that less number of passes would be obtained if longer periods of cooling in a cooling unit are allowed.

In the aspect of the proposed algorithm, the hybrid method was able to solve MIDO problems; however, the computational time is still too expensive. This computational time is mainly needed to solve the dynamic optimization part of the problem (continuous part of the MIDO problem) in every evaluation step of GA. Therefore, an improved strategy to reduce the computational time should be considered in a future work.

5.1.3 Comparison of the synthesis problem using empirical model and theoretical model

- There is a need of a different empirical model for each particular unit represented in a rice drying process for the synthesis problem using empirical model while only one drying model developed from the principles of mass and energy balances is required for the synthesis problem using theoretical model.

- The synthesis problem using the theoretical model has a potential to analyze more alternative choices of drying configurations embedded in the superstructure than the empirical model.

- Empirical models lead to simpler mathematical functions which give rise to an optimization problem dealing with the set of algebraic equations and are able to be solved in commercial optimization software (e.g. GAMS). The theoretical model is more complicated mathematically and gives rise to an optimization problem that deals with a set of differential algebraic equations (DAEs). There is no generic approach to solve this particular problem; therefore the hybrid method was proposed to solve the problem in MATLAB.

- Computational time from solving the synthesis problem using the empirical models in GAMS is significantly less than the time from solving the synthesis problem using the theoretical models with the proposed algorithm in MATLAB.

- The results from the synthesis problem using the theoretical model provides a more detailed analysis and better insight of rice drying processes when compare to the empirical model.

5.1.4 Contribution of this research

- An overview of using different types of drying models for the synthesis problem of rice drying processes was illustrated.

- The issues related to using mathematical programming approaches to the synthesis problems with different types of process models (empirical and theoretical) were addressed.

- Guidelines for optimum drying configurations and operating conditions for various ranges of drying operations found in practice were provided.

- An optimization method for solving multistage mixed-integer dynamic optimization problem was proposed.

- Further extensions of research for the synthesis problem of rice drying processes were discussed.

5.2 Recommendations

- A strategy to reduce the computational time of the proposed hybrid method to solve the MIDO problem should be considered, i.e. perform the parallel computing of GA in multiprocessor computers.

- From using the theoretical model with the synthesis problem we found that quality degradation of rice grain is due mainly to the choice of operating conditions but not from the choice of process configurations; therefore, more detailed analysis for finding the global optimality of operating conditions for an existing drying configuration found in real practice should be carried out.

- There is a need for the development of a more involved energy objective function which takes other operating variables related to the use of energy in real rice drying process into account other than only the air temperature.

- There is a conflict between two objective functions; an attempt to lower the energy consumption results in a lower yield of head rice while an attempt to increase the yield of head rice requires more energy consumption. Thus multi-objective optimization should be considered to take the trade-off between those two objectives into account.

- The application of GDP framework to integrate a choice of process models (valid in a different range of operations) into the synthesis problem of any particular process should be extended.

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