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Decision support for evaluating energy demand in vinification processes using fuzzy sets theory

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Abstract

The current trend associated with high energy demand, depletion of energy reserves and low potential of renewable energy sources linked with strong industrial growth, is increasingly becoming unsustainable. As a result, production costs have increased considerably in the process industries, mainly owing to skewed energy demand and supply realities. A feasible strategy for meeting these challenges is to reduce energy consumption per unit throughput. However, to obtain a workable solution, decision makers may have to deal with energy management variables that are ambiguous, which makes solving the energy minimization problem with conventional numerical approaches very difficult. In this paper, we consider an alternative approach based on fuzzy logic to qualitatively evaluate the energy demand associated with an industrial cooling process. The model was formulated based on Mamdani fuzzy logic inferencing and implemented in MATLAB 6.5 via the Fuzzy Logic toolbox. The energy demands pertaining to specific variables were independently estimated, followed by an estimate of the overall energy consumption. The procedure is demonstrated via a case study of cooling at the maceration stage of a vinification process in the wine industry.

Keywords: fuzzy logic, energy minimization, vinification, wine industry, maceration

1. Introduction

Energy is the lifeblood of economic activities, such as related to transportation, communication and manufacturing of goods and services (Gibbons et al., 1989). Unfortunately, energy production, distribution and consumption often go hand in hand with unsustainable degradation of natural ecosystems (Gibbons et al., 1989; Hunhammar, 1996). This is exacerbated by rampant population growth and the concomittent demand for an improved quality of life by increasing numbers of people. One such indicator of improved quality of life has been the growth of per capita energy consumption (MacNeil, 1989). Since the 1970s, governments, civil society, policy makers and the general public have made numerous calls to the process and manufacturing industries for the adoption of sustainable operating and development strategies in order to minimize their negative impact on non-renewable world resources (MacNeil, 1989; WCED, 1987). These calls reflect an appreciation of the current challenges posed by a rising energy demand, rapidly dwindling fossil energy reserves, the short term prospects of harnessing renewable energy sources on the scale required, as well as the increasing toxic and hazardous waste generated by both domestic and industrial sources.

The energy demand in cooling and heating processes in the wine industry is driven by a number of diverse operations, including the transport and crushing of grapes, pressing of grape skins, pumping of grape juice, mixing and filtering of wine, ion exchange operations, lighting, heating of fermentation tanks, bottling of wine, air conditioning and humidity control in barrel aging, as well as refrigeration of wine at various points of production (Rankine, 1989; Boulton et al., 1998). In practice, refrigeration processes account for more than half of the wine industry's energy demand and peak demand is reached during the grape harvest season. Energy demand depends on the specific process, equipment used, the time of production, as well as other site-specific features, making it difficult to devise generally valid energy minimization strategies for the entire wine industry.

Although first-principle approaches to the modelling of energy consumption in the wine industry have been reported (López and Lacarra, 1999; Niviéré et al., 1994; Hodson, 1991), these methods are not able to capture the complexities of wine production processes, which are not fully understood at present. Likewise, analytical models depending on the measurement of plant variables also tend to be impractical, since many variables critical to plant operation may not be measured to begin with. Instead, wine production facilities are often operated based on heuristics that may not be formulated explicitly. These heuristics are used by plant operators, who have often accumulated their experience over many years. For these reasons, models that can account for uncertainties and partial process knowledge are attractive and, in this paper, the development of a fuzzy expert system to guide the minimization of energy consumption on wineries is considered.

2. Cooling at the maceration stage

The importance of temperature control during the production of wine is well established, particularly in terms of the quality of the wine produced (Jackson and Lombard, 1993; Walker, et al., 1974; Aljibury, 1993; Marais, 1998; Marais, 2001; Smart and Dry, 1989). The temperature profile under which the wine is maintained at any stage of the vinification process depends mostly on the type of grape. For example, production of high quality white wine requires the maintenance of a temperature range of 10°C to 18°C, while the production of red wine needs to be controlled between 15°C and 25°C.

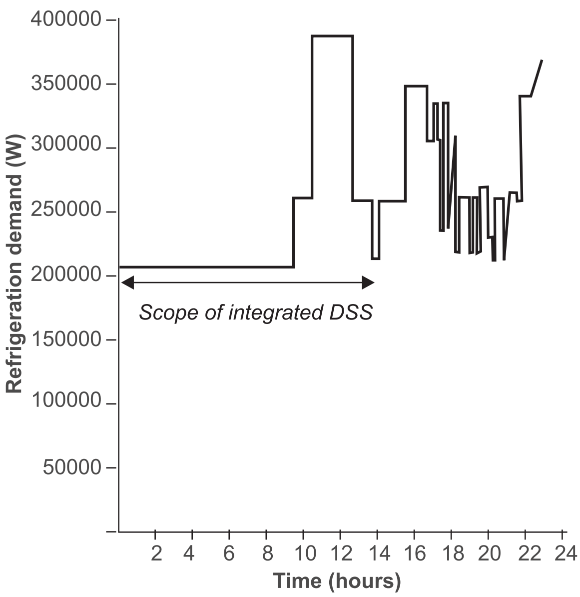

Figure 1: Cooling heat load profile during the maceration process (adapted from [8])

To effectively manage the refrigeration requirements at the maceration stage, it is necessary to identify all sources of heat loads. Figure 1 shows a typical example of the daily cooling needs in a winery during the grape harvest season. The peak with the broadest base corresponds to the energy demand during cooling at the maceration stage of the vinification process (López and Lacarra, 1999).

2.1. Problem definition

Cooling in vinification processes is used to control or retard unwanted enzyme, microbial and chemical reactions (Boulton, 1999; López and Lacarra, 1999). These include must cooling in association with juice draining or skin contact prior to fermentation, cooling of juice before and during fermentation, and cooling of wine during storage periods. Figure 2 shows the processes associated with cooling at the maceration stage. The advantages of better energy management at the maceration stage are two-fold. First, integrated energy management means better control, i.e. lower cost and higher quality product, and second, it also has a considerable influence on the energy management of downstream operations, such as fermentation, stabilization and maturation. The factors influencing refrigeration demand from grape harvesting to the maceration stage are briefly discussed in the following section.

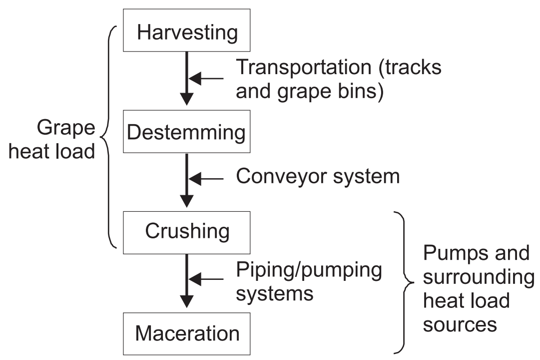

Figure 2: Boundary definition of heat load profile sources contributing towards refrigeration demand at maceration stage

2.2 Energy management

Studies by Rankine (1989) and the United Nations Environmental Programme (UNEP, 1995) have indicated that energy consumption in the wine industry has increased significantly in the last two decades. This is particularly true for cooling and heating applications. To reduce the cooling energy demand during vinification, it is imperative that wine makers adopt integrated solutions and incorporate them appropriately in their operations. Thus, selected control strategies should be able to meet cooling system efficiency requirements without having an adverse effect on the environment. In practice, several heat exchangers are used to control the temperature of the wine in the maceration stage. Typical heat transfer coefficients for the refrigeration of wine are summarized in Table 1, while Table 2 summarizes operational strategies that are used to

Table 1: Heat exchangers used in the wine industry

Type of heat exchanger	*Heat transfer coefficient ($Wm^{-2}K^{-1}$)*	*Reference*
Tank Jackets	12-60	Boulten et al. [6]
Shell and tube	600-900	Boulten et al. [6]
Spiral	760-1060	Ellis [17]
Plate	2400-3600	Boulten et al. [6]
Scraped-surface*	600-2000	Cuevas and Cheryan [18]

** Scraped-surface heat exchanger is only suitable for wine cold stabilization and was not considered in this study*

Table 2: Heat load sources for grapes, must, wine juice and several feasible alternatives of reducing high energy consumption

Heat load type	*Process source*	*Heat load*	*Causing factors*	*Energy minimization alternatives*
Grape heat	Harvesting	Solar energy	Harvesting time Ambient air Temperature	Harvesting of grapes at low temperatures (at night or early morning hours). Immediate grapes cooling after harvesting using carbon dioxide pellets (CO_2). Covering the grape bins as soon as they are filled with grapes.
	Transport-ation	Solar energy	Distance Ambient air Temperature	Cooling of grapes during transportation using CO_2 pellets. Using covers over the grape bins during transportation. Use of natural overnight cooling.
External heat	Maceration	Solar energy	Ambient air Temperature	Insulation of heat exchangers. Air conditioning/ cooling part or entire winery.
		Frictional energy	Frictional forces	Regular lubrication/maintenance of pumps. Switching off motors when not in use. Use of variable speed drives to reduce load on motors.
		Water quality	Biofouling/ scaling/ corrosion	Use of biocides to control or remove scaling or corrosion on pumps. Regular cleaning of pumps surfaces. Use of high quality water for the cleaning of pumps.

minimize energy consumption during vinification.

In hot climate countries like South Africa and Australia, the diurnal ambient atmospheric temperatures vary between 10°C and 40°C in the wine growing regions. Under such environmental conditions, the heat load profile at the maceration stage requiring cooling is affected by both the grape heat load and the external heat load. Maintenance of the grape heat load profile is the most important and a function of the ambient temperature at the time of harvesting and during the transportation of the grapes to the processing wineries. The effectiveness of implementing temperature control depends on mechanisms put in place immediately after the harvesting of the grapes, and the distance over which the grapes have to be transported between the vineyards and wineries. The external heat load at the winery is mostly comprised of the heat from pumps and the surroundings, respectively typically contributing 5-10% and 5-20% of the total grape heat load (Rankine, 1989).

3. Modelling of energy consumption

The proposed model provides a modularised, flexible framework for estimating the overall energy consumption as a function of the different process variables. The overall energy consumption is expressed as an index on a scale of 0-1. The hierarchical relationships between the relevant process variables can be summarized as indicated in Figure 3, based on information gathered from actual winery operations and the open literature. The acquired knowledge was validated using two experts in the South African wine industry.

Within this methodological framework, the overall energy consumption during refrigeration was decomposed into two *primary components*. The first component relates to the configuration of the cooling system and its attendant properties. In this study, these factors were modelled as a function of the heat exchanger used during cooling and expressed in terms of a heat transfer coefficient. The second component is the total heat load profile

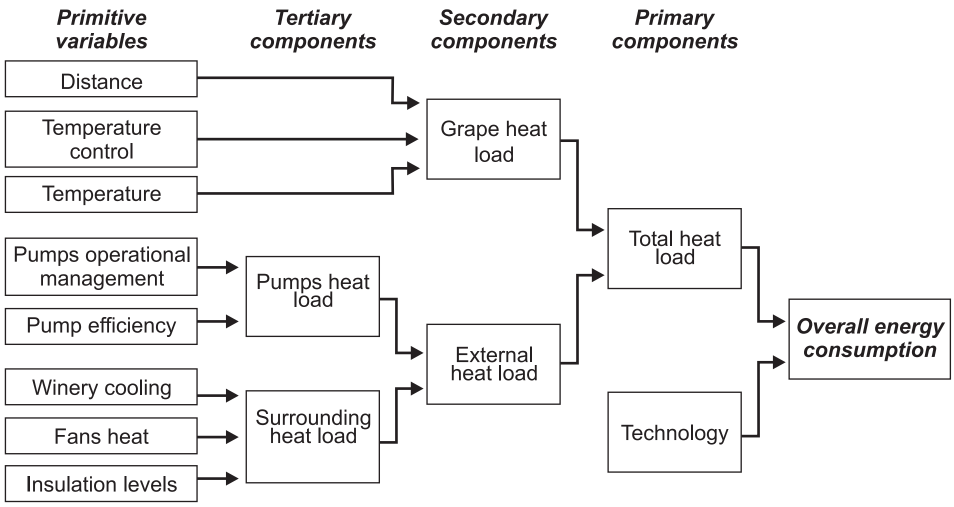

Figure 3: Hierarchical relationships between the process variables influencing the refrigeration energy demand at the maceration stage

required during cooling. The total heat load is very important in cooling installations in wineries and can be controlled by various operational strategies.

In turn, the heat sources are comprised of two *secondary components*, viz. the grape heat load and the external heat load. The grape heat load is controlled by the daily weather variations of a given region and operational mechanisms adopted to reduce the heat load of the grapes at the time of harvesting and during transportation to the wine processing winery. In this work, the *primitive variables* used in evaluating the grape heat load profile were the temperature control, ambient atmospheric temperature and transportation distance between the vineyards and the processing wineries. The external heat load refers to the heat absorbed by the grape juice and must during crushing and pumping.

In this model, external heat load was evaluated using two *tertiary components*, namely the heat load profiles from the pumps and from the surroundings. Pump heat load was generated by the distribution pumps, owing to the pumping of wine and must through the heat exchangers and associated piping network. This heat load was a function of the *primitive variables*, viz. pump operational management and pump efficiency. Each of these primitive variables represented a number of basic factors, such as frequency at which pump surfaces were lubricated to ensure that no pressure drop occurred on the pumps, extent of biofouling of the surfaces, etc.

The surrounding heat load referred to the heat transferred from the ambient air into the must or grape juice through the piping system or the heat exchanger itself. Control of the heat gained from the surroundings could be realized through three primitive factors, namely the insulation of heat exchangers, cooling of the winery, as well as use of efficient fans (air conditioners). For instance, in a case where the insulation of the coolers was effective, the heat gained from the surroundings was drastically reduced, while poor insulation resulted in high heat gains.

4. Fuzzy modelling of energy consumption

Decisions with regard to energy consumption during the cooling process at the maceration stage have to take place under conditions of considerable uncertainty, owing to an incomplete understanding of the process. Under these conditions, fuzzy models provide a convenient framework for models that can deal with ambiguity or partial process knowledge (Zadeh, 1965; Zimmermann, 1991).

4.1. Rule base

The core of a fuzzy rule-based system consists of the rule base used for storing knowledge acquired from experts or documented literature in a specific domain. An inference engine is responsible for fuzzification of numeric (crisp) inputs, fuzzy reasoning and defuzzification of the output. The rules expressing the inputs and outputs of each knowledge base are expressed symbolically in the form of words or phrases of a natural language as linguistic variables and fuzzy sets (Özge Uncu and Türksen, 2004; Rankine, 1989). An example of such an IF-THEN rule is

IF PUMP EFFICIENCY is low **AND** PUMP OPERATIONAL EFFICIENCY is *poor*
THEN PUMP HEAT LOAD is *very large*

The computation of the overall energy consumption involved the initialisation of certain primitive variables by the user or composite computed values from other knowledge bases. The outcomes from the different knowledge modules were then combined to yield composite values as output to the next level and the process continued until the final overall energy consumption could be estimated.

This approach is analogous to consulting several experts on a certain problem and then deriving a final conclusion based on each individual opinion. The model is flexible and can allow a user to choose initial values or adjust the rules in any knowledge base on the basis of operational realities for a specific winery.

4.2. Fuzzy inferencing

The inferencing mechanism is used to compute the fuzzy system output and is comprised of four steps, namely normalization, fuzzification, inferencing and defuzzification. A schematic summary of the process is presented in Figure 4. In each module, qualitative inputs were assigned numerical values, while the values of measurable variables were entered as they are. Numeric values were obtained for the primitive variables by aggregating all the user responses and then normalizing the output values on a defined scale of 0 to 1 or 0 to 100. Aggregation and normalization of the numerical inputs were based on the arithmetic mean of the values.

Once all the inputs had been normalized to appropriate numeric values, they were fuzzified. Fuzzification entailed the assignment of a degree of membership, μ, ranging from 0 to 1. Trapezoidal membership functions were used to fuzzify the input variables, as indicated in Figure 5, while both trapezoidal and triangular membership functions were used for the output variables. For example, a transportation distance of 40 km would be considered between short and average and would therefore be assigned non-zero membership values of 0.6 and 0.4 for the classes *short* and *average*, respectively and a zero membership function value for *long*, as it would definitely not be considered to be a long distance.

In total, nine input variables were used in the system. These variables and their designated membership functions are summarized in Table 3.

The inference engine is the core component of the inferencing mechanism in a fuzzy system. This is because it controls the reasoning path of the system, flow of data in the modules and then manipulates the input data based on the expert knowledge coded as rules in the fuzzy knowledge bases. The inference engine then integrates and aggregates results from various modules to derive the final decisions and conclusions for a targeted system output, in this particular case, the overall energy consumption. The fuzzy inferencing engine is supported by the knowledge base, which represents all different operating conditions and a spectrum of all possible system outcomes. The knowledge base contains the database and the fuzzy rule base. The fuzzy rule base was used in storing the fuzzy if-then rules as expert knowledge by aid of membership functions.

On the other hand, the database contains qualitative and quantitative data crucial for evaluating processes and procedures that govern the cooling energy demand. In addition, it contained mathematical linear models for averaging and ultimately normalizing the input variables into their respective universes of discourse.

Several methods of fuzzy inferencing are used in practice, but the most popular ones appear to be the so-called MAX-MIN method and the MAX-DOT or MAX-PROD method (Lee, 1990). In this case, the MAX-MIN method (Mamdani, 1974) was used, where the fuzzy output variables are clipped at the truth value generated by the premise of the rule, so that the area under the clip line constitutes the outcome of the rule. Figure 6 illustrates fuzzy inferencing using the Mamdani model (Mamdani, 1974). The final stage of the fuzzy inferencing operation is defuzzification, used to convert the fuzzy member-

Table 3: Linguistic input variables, fuzzy sets, and crisp intervals

Input parameter	Membership functions, their linguistic variables and break points
Grape temperature	Low (0,0,15,20), Medium (15,20,25,30), High (25,30,40,40)
Temperature control	None (0,0,0.3,0.4), Partial (0.25,0.4,0.55,0.75), Effective (0.55,0.7,1,1)
Transportation distance	Short (0,0,30,50), Average (30,60,80,120), Long (80,110,150,150)
Pump efficiency	Low (0,0,20,40), Medium (20,40,60,80), High (60,75,100,100)
Pump operational management	Poor (0,0,20,30), Fair (15,30,40,55), Good (40,55,65,80), Excellent (65,75,100,100)
Fans heat	None (0,0,0.2,0.4), Medium (0.2,0.45,0.65,0.8), High (0.65, 0.85, 1,1)
Insulation levels	Poor (0,0,0.2,0.4), Fair (0.2,0.4,0.6,0.8), Good (0.6,0.8,1,1)
Winery cooling	None (0,0,0.1,0.3), Slightly (0.1,0.3,0.5,0.7), Sufficient (0.5,0.7,1,1)
Heat transfer coefficient	Very low (0,0,300,800), Low (400, 600, 800, 1000), Moderate (800,1100,1500,1800) High (1500,1800,2300,2500), Very high (2300,2500,3500,3500)

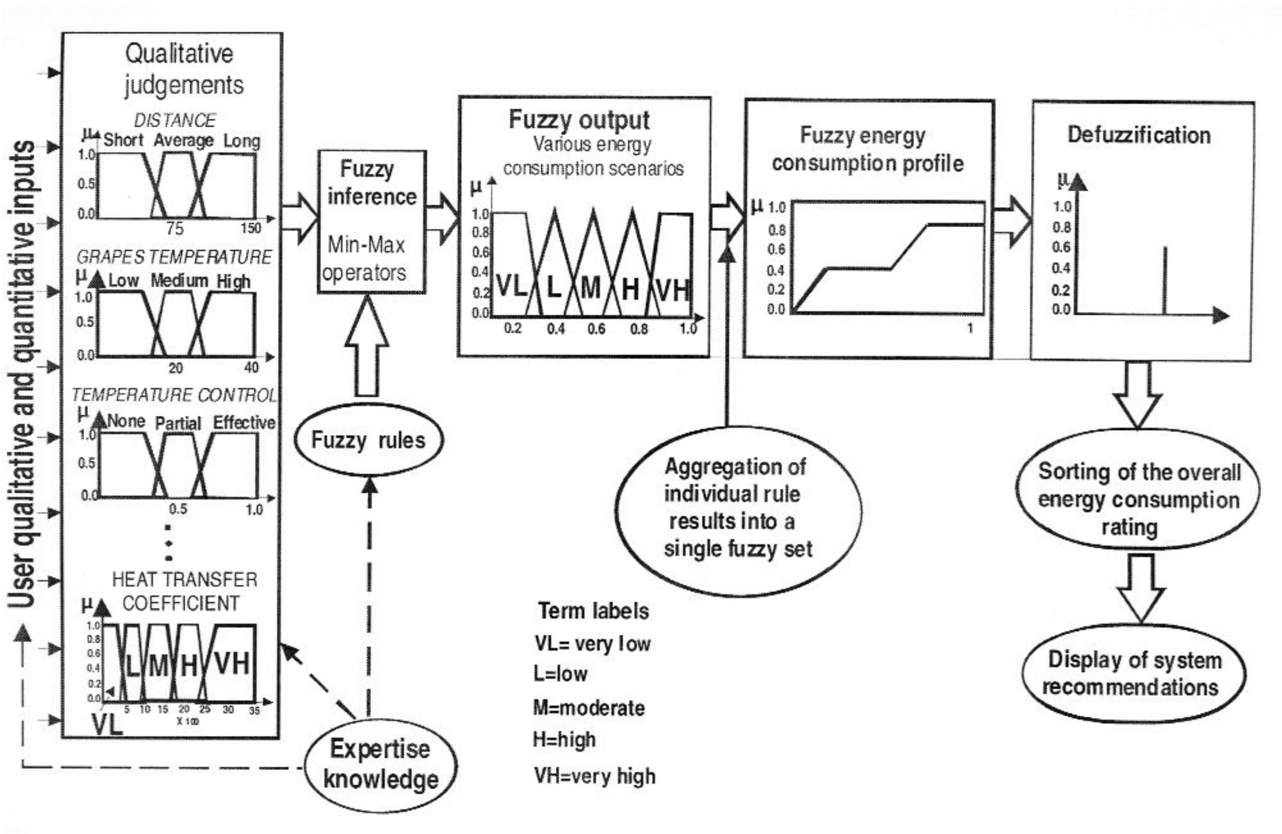

FIgure 4: Configuration of fuzzy inferencing process

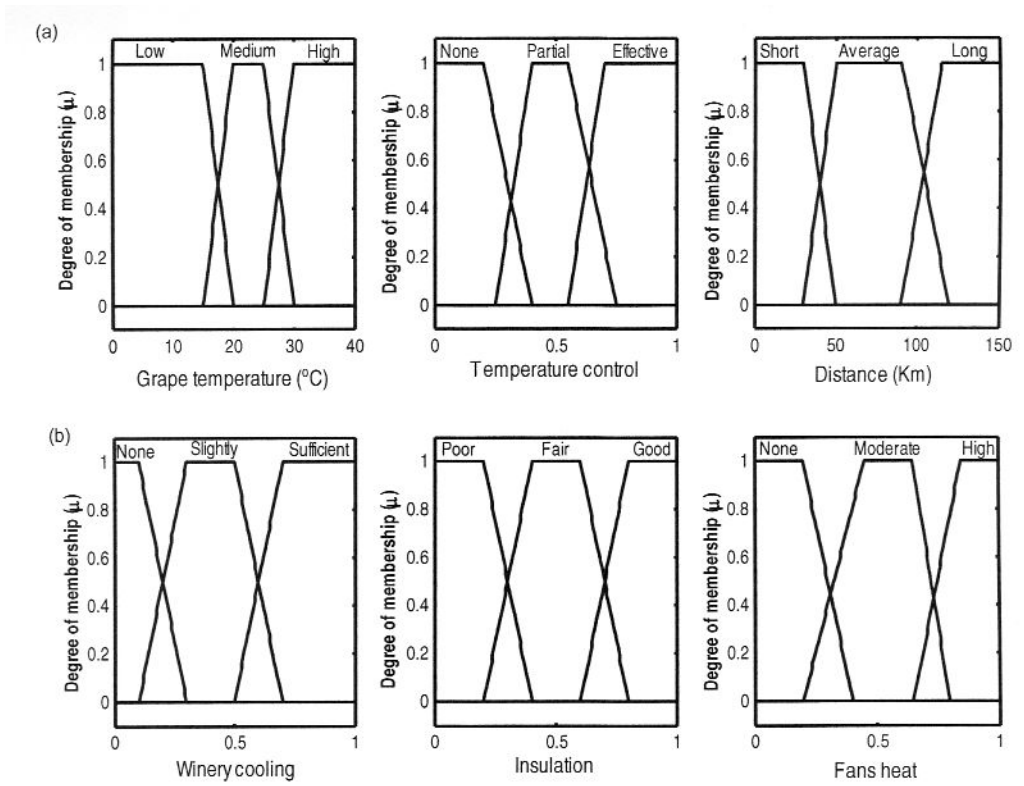

Figure 5: Examples of trapezoidal membership distribution functions defining linguistic input variables for evaluating (a) grape heat load and (b) surrounding heat load

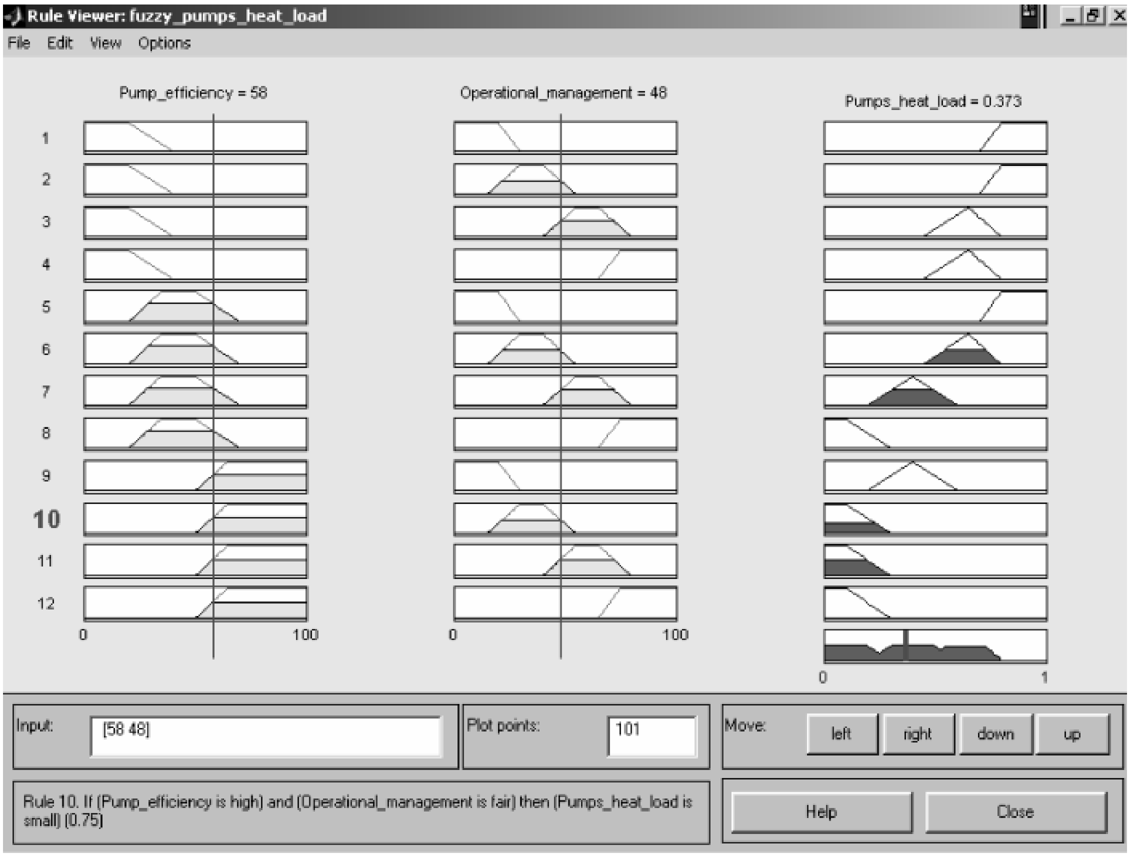

Figure 6: Generation of system diagnostics and decisions at the pump heat load module through fuzzy inferencing mechanisms

ship grades of the output into a single numeric output value (Mamdani, 1974; Yager and Filev, 1993; Braae and Rutherford, 1978; Hellendoorn and Thomas, 1993). The centroid method was used to do so in this study.

For example, the quantity of pump heat load was determined by evaluating the centre of area (see Figure 6), where a single output value of 0.373 was obtained. In this investigation, the defuzzified numerical values served two purposes.

First, the defuzzified values generated from the primary heat load sources were used as secondary system inputs to compute the external heat load and the total heat load (see Figure 3) requiring refrigeration. Second, the final defuzzified value was also interpreted as an index for the quantity of energy consumed during the maceration process. Thus, it helped to classify the quantity of electrical energy consumption using the fuzzy set theory in the interval 0 (minimal energy consumption) to 1 (maximal energy consumption). This index represents the integrated overall performance of all the processes prior to and during the refrigeration process at the maceration stage. The index is a useful indicator to the winery management of the extent of energy consumption as a function of operational and technological factors for a given batch at the maceration stage.

4.3. Linguistic rules

The energy consumption model discussed in section 3 was used to develop a series of small knowledge bases representing the heuristics or principles governing the control of energy consumption during cooling at the maceration stage. The configuration of the fuzzy model is shown in Figure 3. The model consists of tree-like hierarchy of knowledge rule bases, as indicated in Figure 7.

The simulation of the evolution of the overall system was represented by IF-THEN rules coded into the knowledge bases. The rules defined the interrelationship among various linguistic input variables and the corresponding module output. The IF-THEN rules offered a feasible alternative to linking the input variables shown in Table 3 and to compute an overall energy consumption index. The development of the rules in the knowledge bases was done via interviews of experts and plant operators, questionnaires and a survey of public domain literature. Collectively, these rules represented the process model. For example, Figure 8 is the 3D response surface plot showing the relationship between the input variables total heat load and heat transfer coefficient and the output variable overall energy consumption index.

On the basis of a premise that only one linguistic variable defines each input variable granulated

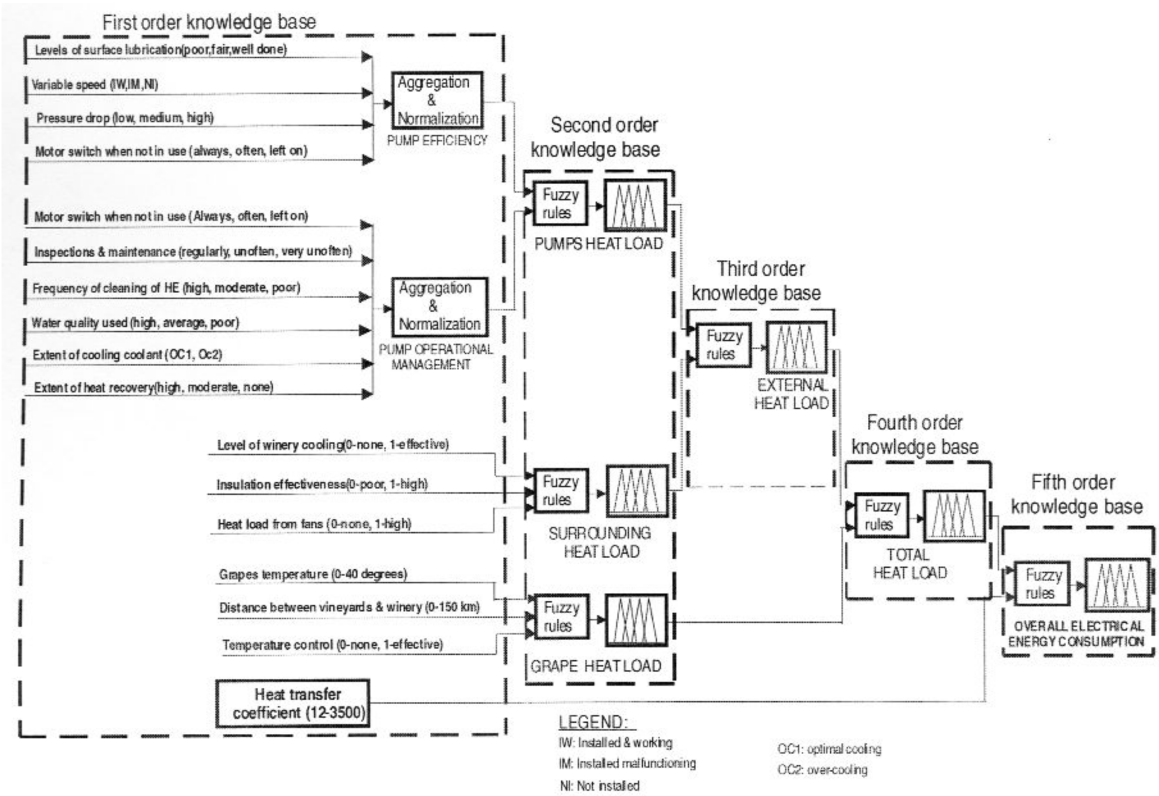

Figure 7: The hierarchical modular structure of the fuzzy model for the evaluation of energy consumption

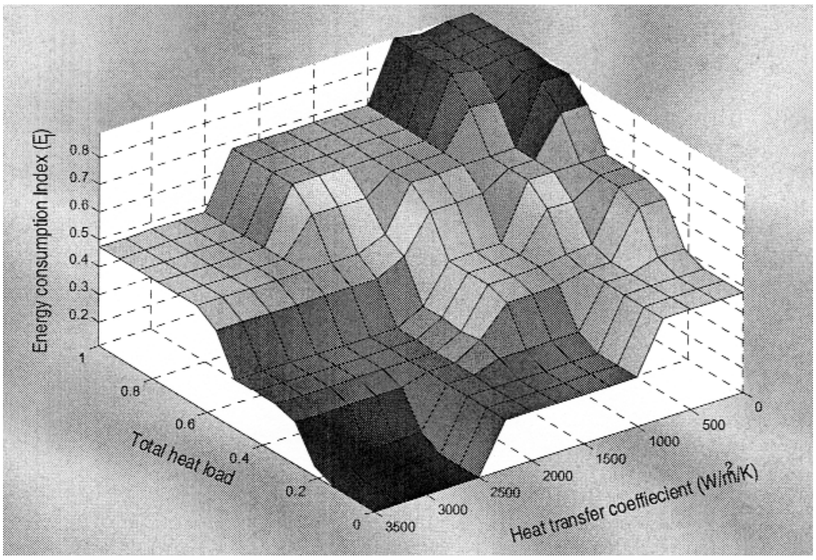

Figure 8: A 3D output response surface simulating the input variables 'total heat load' and 'heat transfer coefficient' to compute the output variable 'overall energy consumption index' as modelled by the fuzzy model

into several fuzzy sets, it became apparent that two different approaches were possible in designing the IF-THEN rules and subsequently incorporating them into the knowledge base. The first option was to involve the construction of an aggregate set of rules combining the nine linguistic variables simultaneously to evaluate the overall energy consumption. However, this approach was impractical, since the option would have required the development of a single knowledge base of 43,740 ($3^7 \times 4 \times 5$) rules. Apart from the exorbitant development cost, such a large knowledge base would also be difficult to maintain and validate.

For this reason, a series of smaller and more compact modules yielding simpler and fewer rules in each knowledge base was constructed. This meant that only two or three variables were analysed at the same time. With this approach, customizing the knowledge rule base to satisfy specific winery constraints is easy.

To illustrate the specificity of a given module, we consider the evaluation of heat load from pumps. In this case, the output was computed using two linguistic input variables, i.e. the pump efficiency and pump operational management, having three and four fuzzy sets, respectively. As a result, this particular module had a rule base of $3 \times 4 = 12$ rules. The rules in the module for computing the pumps heat load are summarized in Table 4. A similar approach was used to determine the output to the rest of the modules. The number of rules in the other fuzzy modules were as follows: Heat load from the grapes (27), the surroundings (15) and effective external heat load profile (16). The total heat load (20) was evaluated from the results of the grape and external heat load profiles. By considering the total heat load and the heat transfer coefficient, a rule base of 25 rules was constructed to compute the overall energy consumption. Using the cascading modular approach, the entire fuzzy model had a total of 115 fuzzy rules, as indicated in Appendix 1 (Tables A.1 to A.5). The resultant fuzzy expert system proved easy to construct, maintain and modify, since each module could be refined and tested independently before incorporation into the knowledge base structure. This flexibility enhanced the addition of new knowledge into the system without the need to modify the entire knowledge base.

In evaluating the linguistic rule base for the determination of the surrounding heat load, certain domains in the input variable space were found impermissible. This meant that the rules in the particular module were pruned from 27 (3^3) to 15 (as we had 3 fuzzy sets for each of the three linguistic input variables). The consistency of pruning the rules in the rule base was achieved using two heuristics:

- If winery cooling did not exist (*none*) in a certain winery, but the rule asserted that the heat from the cooling fans assumed the fuzzy set values: *average or high*, then such a rule was viewed as impermissible.
- If there were winery cooling and the efficiency of the cooling fans could not be 100%, then the heat dissipated by the fans could not be described as *none*. Under such a scenario, a rule that asserted that winery cooling could assume the values *effective* or *slightly* when the heat from the fans was regarded as *none*, was also deemed to be infeasible.

4.4 System implementation and validation

The prototype fuzzy expert system was developed with the MATLAB® fuzzy logic tool box (The Mathworks, 2002a), integrated with MATLAB® technical computing environment (The Mathworks, 2002b). An interactive graphical user interface (GUI) supported by MATLAB® facilitated the coding of the acquired knowledge in the rule bases. The GUI also served as a dialog-interface for the user to initialise the evaluation of feasible energy consumption strategies under given sets of operating conditions.

The prototype fuzzy expert system is currently undergoing a validation process by developers and domain experts in industry. Through this process, knowledge in various modules is being tested for accuracy and completeness to maximize its potential usefulness in assisting decision makers in the wine industry to minimize energy consumption prior to and during wine cooling at maceration stage.

Table 4: Linguistic IF-THEN rules in the pumps heat load knowledge base module

	IF	***AND***	***THEN***	
Rule no.	*Pumps operational management*	*Pumps efficiency*	*Pumps heat load*	*Rule weight*
1.	Poor	Low	Very low	1.00
2.	Poor	Medium	Very low	0.75
3.	Poor	High	Moderate	1.00
4.	Fair	Low	Very low	1.00
5.	Fair	Medium	Low	1.00
6.	Fair	High	Small	0.75
7.	Good	Low	Low	1.00
8.	Good	Medium	Moderate	1.00
9.	Good	High	Small	1.00
10.	Excellent	Low	Low	0.75
11.	Excellent	Medium	Small	0.75
12.	Excellent	High	Small	1.00

5. Case study

In this case study, the overall energy consumption under four different operating scenarios are compared and the significance of adopting an integrated approach towards energy management is highlighted. Table 5 summarizes both the qualitative and quantitative user inputs. In column 1, user inputs 1 to 4 relate to the evaluation of the pump efficiency from the qualitative inputs, while inputs 4 to 9 determine the operational management of the pumps before and during the cooling process. Using the assigned fuzzy numbers to the qualitative inputs, the heat load attributable to the pumps is then computed. Numbers 10 to 12 provide quantitative input values for the determination of the heat load of the surroundings, while from 13 to 15, the inputs facilitate the computation of the grape heat load. Input 16, together with the total heat of the system evaluated from inputs 1 to 15 are used as fuzzy input variables to evaluate the overall energy consumption index. After coding the user inputs, the fuzzy model performs several computations to ensure that the acquired knowledge is transformed into a format suitable for the fuzzy inference engine. On the basis of the user inputs outlined above, the fuzzy model generated the results presented in Table 6.

Table 5: User data inputs for the worked scenarios

	User information required inputs	*Scenario 1*	*Scenario 2*	*Scenario 3*	*Scenario 4*
1.	Levels of surface lubrication (poor, fair well done)?	Fair	Poor	Well done	Well done
2.	Variable speed installation pumps (Installed & working well (IWW), Installed & malfunctioning (IM), Not installed (NI))?	IWW	NI	IM	IM
3.	Pressure drop due to biofouling (low, moderate, high)?	Moderate	Moderate	High	High
4.	Switch-off frequency of motors after use (always off (AO), often off (OO), left on (LO)?	LO	OO	AO	AO
5.	Frequency of inspections and maintenance of pumps (regularly, unoften, very unoften (VU))?	VU	VU	Regular	Regular
6.	Frequency of cleaning the heat exchangers (high, moderate, low)?	High	Low	High	High
7.	Quality of water used for cleaning the heat exchangers (high, moderate, low)?	Average	High	Average	Average
8.	Extent of cooling the coolant (very low temperature (VLT), optimal temperature (OT))?	OT	VLT	VLT	VLT
9.	Extent of heat recovery strategies implementation in a facility (none, moderate, high)?	High	None	Moderate	Moderate
10.	Levels of winery cooling (0-none, 1-effective)?	0.2	0.5	0.8	0.8
11.	Effectiveness of insulating pipes and surfaces (0-poor, 1-good)?	0.6	0.35	0.2	0.2
12.	Temperature of the grapes at the time of harvesting fans (0-none, 1-high)?	0.4	0.75	0.3	0.3
13.	Temperature of the grapes at the time of harvesting (Range 0-40 °C)?	27	30	15	15
14.	Distance between winery and the vineyards (Range 0-150 km)?	18	67	10	10
15.	Extent of temperature control during after harvesting and during transportation (0-none, 1-effective)?	0.4	0.4	0.5	0.5
16.	Heat transfer coefficient of the heat exchanger (Range 0-3500 $W/m^2/K$)	850	75	2750	60

Table 6: System analysis results based on the user inputs in Table 5

Scenario	*PE Index*	*POE Index*	*PHL Index*	*SHL Index*	*EHL Index*	*GHL Index*	*THL Index*	*OEC Index*	*System Scenario*
1.	50	66.1	0.376	0.608	0.650	0.422	0.475	0.6150	High
2.	33.3	50	0.574	0.682	0.831	0.633	0.849	0.7588	Very High
3.	66.7	87.7	0.106	0.400	0.350	0.116	0.116	0.1141	Very Low
4.	66.7	85.7	0.106	0.400	0.350	0.116	0.116	0.5000	Moderate

Scenario 1

In scenario 1, the results show a high energy demand during the refrigeration process. Examining the operating conditions specified in Table 5 and the fuzzy model output shown in Table 6, the tool assists the decision makers to identify areas where improvements can be made to reduce the high consumption. Some of the solutions in this case would be to improve the pump efficiency through more effective lubrication of the pump surfaces, switching off the machines after use and eliminating the growth of biofoulants. The surrounding heat load index is ranked high, owing to poor management of the winery cooling, as indicated by the inputs of the user. Consequently, though the model ranks the pump heat load as moderate, the effective external heat load was computed as high because of high heat load from the surroundings.

Furthermore, the low heat transfer coefficient suggests that a shell and tube or spiral heat exchanger was used to refrigerate the wine juice and the must. This resulted in high energy consumption in order to cool the throughput to the desired product temperature. However, in view of the high capital cost requirement to replace the heat exchangers, the most feasible cost effective alternative rests on improving operational-oriented strategies in this particular case.

Scenario 2

In Scenario 2 little attention is given to minimizing high energy consumption through proactive interventions during harvesting, transportation and cooling processes. This is indicated by the low values of the pump and operational efficiencies shown in Table 5. Combining these results with other user inputs, the fuzzy model determined the heat loads from the pumps and surroundings as moderate to large and medium to high, respectively. Similarly, the grape heat load was ranked as high, owing to high ambient temperatures, a reasonably long transportation distance and negligible temperature control of the grapes during this period. High heat loads from the environment (with an index of 0.831) and the grapes (with an index of 0.633) led to the total heat load to be ranked very high (with index of 0.849).

The low value of heat transfer coefficient can probably be attributed to an inefficient heat exchanger, e.g. tank jackets characterized by poor heat transfer. To compensate for this inefficiency in the maintenance of the required wine temperature, very low refrigerator temperatures were consequently used to provide adequate cooling. Such a high energy demand can be considerably reduced by adopting integrated approaches, such as improving operation, as well as low cost modification of the heat exchangers.

Scenarios 3 and 4

Scenarios 3 and 4 illustrate how well managed processes complemented by use of efficient heat exchangers can have a positive effect on energy consumption per unit throughput during the cooling process. On the basis of the user responses in Table 5, it is clear that the heat loads from different sources were effectively managed, as the final total heat load was ranked as very low (with an index of 0.116). This can be attributed to the adoption of integrated management of processes and unit operations before and during the cooling process, in addition to ensuring the efficient operation of all equipment.

In scenario 3, a heat exchanger with a very high heat transfer coefficient was used (probably a plate heat exchanger). Under these conditions, the coolers do not require low refrigeration temperatures to achieve and maintain the desired wine processing temperatures. As result, the fuzzy model in the fifth knowledge base computed the overall energy consumption as very low (with an index of 0.1141) based on the high heat transfer coefficient and very low total heat load. However, by changing the heat transfer coefficient from 2 750 $W/m^{-2}K^{-1}$ in scenario 3 to 60 $W/m^{-2}K^{-1}$ in scenario 4, and keeping all other user inputs constant, the energy demand increased by order of a magnitude. From these results, it shows that the type of heat exchanger used for cooling of the wine can have a significant influence on the overall energy consumption.

In summary, the fuzzy logic expert system considered in this study is a useful tool for making decisions with regard to energy conservation in the wine industry, particularly at the maceration stage. Use of the tool does not depend on complex mathematical formalisms, but are calculated by means of fuzzy rules embedded in a hierarchically structured knowledge base using simple natural language. The advantage of this is that the targeted users are likely to accept the recommendations of the system, since it is based on a small number of clearly formulated rules and the user has the opportunity to trace the chain of logic to understand the reasoning behind the suggestions offered by the system.

6. Conclusions

This paper has considered the development of a computer-aided decision support tool for energy management in wineries. The suitability of the tool was evaluated by way of a case study based on energy minimization at the maceration stage of a vinification process. Consideration of actual scenarios in the wine industry suggests that the tool can yield reliable analyses of energy consumption, thereby significantly reducing the time and effort required for such studies.

The use of fuzzy logic made it possible to take into account non-quantifiable factors such as winery cooling, frequency of pump inspections, etc., and the inclusion of qualitative factors such as these played a major role in the development of an effective decision making tool. This is an important practical advantage, in that information with respect to various factors regarding energy conservation is often available, although not with sufficient precision to develop a well-posed numerical model. Current quantitative techniques which fail to use such important knowledge or to use it in an ad hoc manner tend to be less reliable.

Moreover, the system ensures that the decision maker is fully aware of the potential consequences of his or her decisions with regard to energy consumption, often leading to a better understanding of subsequent operational and technical issues. This has been illustrated by four worked scenarios. Each scenario yielded results which were found consistent with industrial practices. Since a modular approach was used to represent process knowledge, the system can easily be adapted or upgraded as more process knowledge becomes available.

Although limited validation of the system has been done at present, it is envisaged that current trends of better instrumentation and improved data logging systems in many wineries will allow more rigorous verification of the system. Also, with the availability of more quantitative data, the design and configuration of the rules could be automated, for example, by using the adaptive network fuzzy inference system (ANFIS) [(The Mathworks, 2002b) or other neurofuzzy methods (Harris et al., 1996; Özge Uncu and Türksen, 2004). This would provide a more principled approach to adapting the system to any winery set-up, regardless of its size and product ranges. Further research is currently focusing on other vinification processes, such as fermentation, stabilization, storage and bottling where cooling is essential. This will aid the development of a decision tool useful for integrated energy management across the entire wine industry.

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Appendix

Table A1: Linguistic IF-THEN rules in the grape heat load knowledge base module

Rule No.	***If*** *Temperature*	***And*** *Temperature control*	***And*** *Distance*	***Then*** *Grape heat load*	*Rule weight*
1.	Low	None	Short	Low	1.0
2.	Low	None	Average	Moderate	0.8
3.	Low	None	Long	Moderate	1.0
4.	Low	Partial	Short	Low	0.7
5.	Low	Partial	Average	Low	0.7
6.	Low	Partial	Long	Low	1.0
7.	Low	Effective	Short	Low	1.0
8.	Low	Effective	Average	Low	1.0
9.	Low	Effective	Long	Low	0.9
10.	Medium	None	Short	Moderate	1.0
11.	Medium	None	Average	High	0.8
12.	Medium	None	Long	Very High	0.8
13.	Medium	Partial	Short	Low	0.4
14.	Medium	Partial	Average	High	0.5
15.	Medium	Partial	Long	High	1.0
16.	Medium	Effective	Short	Low	0.6
17.	Medium	Effective	Average	Moderate	1.0
18.	Medium	Effective	Long	Moderate	0.6
19.	High	None	Short	Very High	1.0
20.	High	None	Average	Very High	1.0
21.	High	None	Long	Very High	0.8
22.	High	Partial	Short	High	0.8
23.	High	Partial	Average	High	1.0
24.	High	Partial	Long	High	0.8
25.	High	Effective	Short	Moderate	1.0
26.	High	Effective	Average	High	0.7
27.	High	Effective	Long	High	0.8

Table A2: Linguistic IF-THEN rules in the surrounding heat load knowledge base module

	If	*And*	*And*	*Then*	
Rule no.	*Winery cooling*	*Insulation*	*Fans heat*	*Sorrounding heat load*	*Rule weight*
1.	Sufficient	Poor	Moderate	Medium	0.7
2.	Sufficient	Poor	High	High	0.7
3.	Sufficient	Fair	Moderate	Medium	1.0
4.	Sufficient	Fair	High	Medium	0.8
5.	Sufficient	Good	Moderate	Low	1.0
6.	Sufficient	Good	High	Low	0.8
7.	Slightly	Poor	Moderate	High	0.8
8.	Slightly	Poor	High	Very High	0.9
9.	Slightly	Fair	Moderate	High	0.7
10.	Slightly	Fair	High	High	1.0
11.	Slightly	Good	Moderate	Low	0.9
12.	Slightly	Good	High	Medium	1.0
13.	None	Poor	None	Very High	1.0
14.	None	Fair	None	Very High	0.6
15.	None	Good	None	Medium	0.8

Table A3: Linguistic IF-THEN rules in the external heat load knowledge base module

	If	*And*	*Then*	
Rule no.	*Winery cooling*	*Insulation*	*Sorrounding heat load*	*Rule weight*
1.	Small	Low	Very Low	1.0
2.	Small	Medium	Low	1.0
3.	Small	High	Moderate	0.9
4.	Small	Very High	High	0.5
5.	Moderate	Low	Very Low	1.0
6.	Moderate	Medium	Moderate	0.75
7.	Moderate	High	High	0.8
8.	Moderate	Very High	Very High	1.0
9.	Large	Low	Low	1.0
10.	Large	Medium	Moderate	1.0
11.	Large	High	Very High	0.6
12.	Large	Very High	Very High	1.0
13.	Very Large	Low	Low	0.7
14.	Very Large	Medium	High	0.8
15.	Very Large	High	Very High	1.0
16.	Very Large	Very High	Very High	1.0

Table A4: Linguistic IF-THEN rules in the total heat load knowledge base module

	If	***And***	***Then***	
Rule no.	*Grape heat load*	*External heat load*	*Total heat load*	*Rule weight*
1.	Low	Very Low	Very Low	1.0
2.	Low	Low	Very Low	1.0
3.	Low	Moderate	Very Low	1.0
4.	Low	High	Low	0.6
5.	Low	Very High	Low	0.8
6.	Moderate	Very Low	Low	1.0
7.	Moderate	Low	Moderate	0.6
8.	Moderate	Moderate	Moderate	0.7
9.	Moderate	High	Moderate	1.0
10.	Moderate	Very High	Moderate	1.0
11.	High	Very Low	High	1.0
12.	High	Low	High	1.0
13.	High	Moderate	Very High	0.5
14.	High	High	Very high	0.8
15.	High	Very High	Very High	1.0
16.	Very High	Very Low	Very high	1.0
17.	Very high	Low	Very High	1.0
18.	Very High	Moderate	Very High	1.0
19.	Very high	High	Very high	1.0
20.	Very High	Very High	Very High	1.0

Table A5: Linguistic IF-THEN rules in the overall energy consumption knowledge base module

	If	***And***	***Then***	
Rule no.	*Total heat load*	*Heat transfer coefficient*	*Total energy consumption*	*Rule weight*
1.	Very Low	Very Low	Moderate	1.0
2.	Very Low	Low	Moderate	1.0
3.	Very Low	Moderate	Low	1.0
4.	Very Low	High	Low	1.0
5.	Very Low	Very High	Very Low	1.0
6.	Low	Very Low	High	1.0
7.	Low	Low	Moderate	1.0
8.	Low	Moderate	Moderate	1.0
9.	Low	High	Low	1.0
10.	Low	Very High	Low	1.0
11.	Moderate	Very Low	High	1.0
12.	Moderate	Low	High	1.0
13.	Moderate	Moderate	Moderate	1.0
14.	Moderate	High	Low	1.0
15.	Moderate	Very High	Low	1.0
16.	High	Very Low	Very Low	1.0
17.	High	Low	High	1.0
18.	High	Moderate	High	1.0
19.	High	High	Moderate	1.0
20.	High	Very High	Moderate	1.0
21.	Very High	Very Low	Very High	1.0
22.	Very high	Low	Very High	1.0
23.	Very High	Moderate	High	1.0
24.	Very high	High	High	1.0
25.	Very High	Very High	Moderate	1.0