A Fuzzy – Based Methodology for Aggregative Waste Minimization in the Wine Industry

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1. Introduction

The wine industry generates large quantities of waste annually, including organic solid wastes (solids, skins, pips, marc, etc.), inorganic solid wastes (diatomaceous earth, bentonite clay, perlite), liquid waste (cleaning wastewater, spent cleaning solvents, cooling water), and gaseous pollutants (carbon dioxide, volatile organic compounds, ammonia, sulphur dioxide, etc.) (Chapman et al., 2001; Musee, 2004a; Musee et al., 2007). Several factors give rise to these diverse waste streams (Musee, 2004a; Musee et al., 2007), however, only the most salient ones are highlighted here. Firstly, wine production evolved from a cottage industry to a global industry. Because of their antiquated origin, the design and development of many wineries made no provision for in-plant modern waste minimization (WM) approaches. Secondly, because the wine industry is dependent on an agricultural feedstock (grapes), the resultant waste streams tend to have a high concentration of organic material. This is because the grape feedstock cannot be altered, replaced, or eliminated before the vinification process begins – if the finished wine quality is to remain consistent. And finally, although auxiliary process feedstock, such as filter aids and diatomaceous earth are essential for clarifying the wine, they cannot be incorporated into the final product. Consequently, the clarification agents constitute part of the waste streams generated from the wine industry. In view of these unique constraints facing the wine industry, among others, necessitates the development of appropriate WM strategies to address the waste management challenges facing the wine industry (Musee et al., 2007).
In recent years, there has been continuous pressure on the operating profits of wine makers, mainly owing to increasing competitiveness in the global wine market. This can be attributed to increased variety of wine brands, rise in operational and input material costs, as well as the emergence of an onerous environmental regulatory framework in many wine producing countries (Bisson et al., 2002). Notably, the impact of stringent environmental legislation on the cost of production is expected to continue to be a key determinant in the international competitiveness of wine products (Katsiri & Dalou 1994; Massette, 1994; Müller, 1999). This, and a combination of other powerful intrinsic and external drivers should motivate the wine industry to consider the possibility of incorporating WM strategies as an integral part of wine making processes. As such, the identification and implementation of appropriate WM strategies should be part of the drive to reduce the cost of wine production – particularly in the context of ensuring its future sustainability.

Source: Decision Support Systems, Book edited by: Chiang S. Jao,
ISBN 978-953-7619-64-0, pp. 406, January 2010, INTECH, Croatia, downloaded from SCIYO.COM

In practice, vinification processes are characterized by complex interactions amongst different production processes. As a result, any effective attempt to enhance winery waste management is likely to require a solution comprising of several WM strategies, and implemented concurrently. However, such an undertaking is dependent on the identification of suitable strategies, and secondly, a careful assessment of each strategy to determine its likely influence in addressing the overall WM problem in the wine industry. Moreover, the assessment of each strategy would inevitably entail the use of multiple screening criteria, such as technical feasibility, economic and social imperatives as well as environmental integrity. Unfortunately, the application of different criteria for the ranking of WM strategies is complicated by the lack of quantitative operating data presently available in the wine industry (Musee et al., 2006a).

Nonetheless, to be effective, decision support tools designed to facilitate waste management in the wine industries should ideally be able to exploit the qualitative data available, as these data constitute a vital component of industry knowledge. Fuzzy logic (Zadeh, 1965; Bonissone, 1997; Yen & Lugari, 1998; Ross, 2004) provides such a platform. Previously fuzzy logic has been applied in developing rational solutions for complex real world problems (Bonissone, 1997), and offering interpretable results (Setnes et al., 1998). For example, successful applications of fuzzy logic have been demonstrated in domains such as process design (Huang and Fan, 1995), water quality assessment (Ocampo-Duque et al., 2006), manufacturing (Büyüközkan & Feyzioğlu, 2004), safety (Gentile et al., 2003), sustainability (Phillis & Andriantiatsaholiniaina, 2001; Gagliardi, et al., 2007; Musee & Lorenzen, 2007; Prato, 2007), and hazardous waste classification (Musee et al. 2006b, Musee et al, 2008a; Musee et al, 2008b).

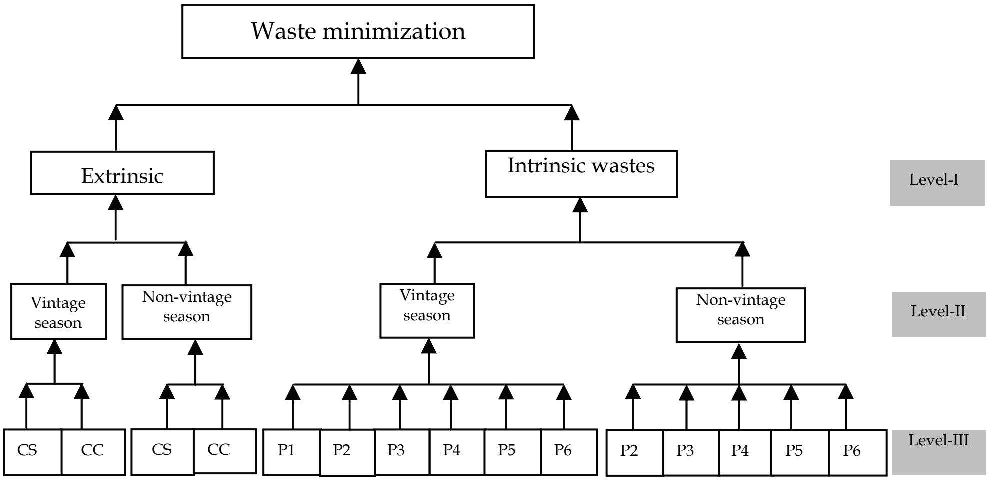
Musee and co-workers (Musee et al., 2003; Musee et al., 2006a) studied a fuzzy logic approach to support decision making in the wine industry that entailed the ranking of WM strategies based on experts' opinions. Because experts hold widely different opinions, this approach yielded decisions associated with a high degree of uncertainty. In the current work, this drawback is addressed using a fuzzy logic framework by combining the ranking of expert opinions with operational data to improve the analysis and selection of WM strategies in the context of wine production. The merits of the proposed approach will be illustrated with two case studies.

This chapter is organized as follows. Section 2 provides an overview of the waste management in the wine industry, and the tools applied to model such a highly unstructured problem. The tools used in modelling the wine waste management problem comprised of; the screening and ranking indices, qualitative reasoning in developing various probable scenarios, and the fuzzy logic. In Section 3, a case study on WM in the wine industry is introduced, where a conceptual model – the intelligent decision support system together with mathematical equations – and how the knowledge stored in different knowledge rule bases were linked to effectively evaluate WM in the wine industry context. Section 4 presents results derived from the model, and a discussion on their application to real-world winery operations with respect to WM. The main findings of the chapter are presented in Section 5.

2. Basics of waste management in the wine industry

2.1 Hierarchical evaluation of wineries

The hierarchical analysis of process systems has its origin in the hierarchical decision approach developed by Douglas (1988). In this chapter, hierarchical analysis was applied to decompose the waste management problem in the wine industry. The vinification process was decomposed into several subtasks, followed by the identification of the most influential variables concerning: (i) the degree of recovery of products and by-products during the production processes; (ii) the quantity and quality of effluent generated during cleaning and sanitization processes; and (iii) the quantity of chemicals consumed during cleaning and sanitization processes.



CS: Cleaning and sanitation; CC: Chemical consumption; P1: Crushing and destemming processes; P2: Transfer processes and operations; P3: Filtration, P4: Pressing; P5: Fermentation; P6: Bottling and packaging.

Fig. 1. Analysis of the vinification processes using a hierarchical approach for the identification of WM strategies.

Fig. 1 depicts a hierarchical model of vinification processes. In this study, the operational variables were decomposed into three levels based on literature survey and interviews with experts knowledgeable on waste management practices and norms in the wine industry. In Level-I, different waste types generated from the vinification processes were classified as intrinsic (process) or extrinsic (utility). Detailed description of waste classification in the wine industry has been presented elsewhere (Musee et al., 2007), and will not be repeated here. In this study, the breadth of the adopted waste classification approach ensured that no waste stream was left unaccounted for. In addition, the model gave rise to consistent and robust results. These aspects will be elucidated in details in Sections 3 and 4.

Owing to the seasonality of the vinification processes and high value-added nature of the product (wine) – wine production is an ideal candidate for both batch and semi-batch manufacturing techniques. This causes a wide variation in the composition of the waste streams - characterized by strong seasonal dependence. In Level-II, the vinification process is characterized by two seasons, viz. the vintage and non-vintage season. It should be noted that a definitive distinction between vintage and non-vintage season is more or less dependent on the processes that take place during a given period on the vinification calendar (Chapman et al., 2001).

The vinification process was further decomposed based on the seasonality of the wine production which led to the identification of the most predominant processes under each season as described in Level-III (see Fig. 1). The next task was to identify how each process, for instance; crushing and destemming, fermentation, or filtration, etc., contributed to the final waste matrix in a given vintage season. A close scrutiny of the waste streams indicated that the final effluent quantity and composition, product and by-products losses, as well as the quantity of chemicals consumed had a strong dependence on the vinification season, as well as the processes operated in a given season. And the final task entailed the development of a systematic approach for identifying WM strategies under each process. The adopted methodology comprised of a three-step sequential approach, namely; waste source identification, qualitative waste causative analysis, and the formulation of feasible alternatives for WM in the wine industry (Musee, 2004; Musee et al., 2007).

2.2 Screening and ranking index

In an earlier study (Musee et al., 2006a), experts were asked to rank the WM strategies based on their waste management experience in the wine industry. However, the approach was found to be cumbersome, owing to the large number of strategies to rank (see details in Musee et al., 2007). This resulted in inconsistencies in the final ranking of WM strategies. This drawback is addressed in this chapter by using a more rigorous ranking approach that includes the use of a WM index (WMI). The WMI was used to assign dimensionless scores to each strategy in terms of its overall potential degree of influence on a specific targeted system output (e.g. chemical usage, effluent quality, etc). The WMI was more effective than the less formal approach previously reported by Musee et al. (2006a), because the influence of the experts' subjective perceptions or personality aspects were eliminated.

Generically, the evaluation criteria for WM alternatives often use economic functions which often lead to unintended consequences of identifying suboptimal solutions. Another demerit of relying solely on economic criteria lies in their inherent bias for identifying inferior alternatives purely based on cost. These criteria tend to favour options geared towards waste treatment above those that promote waste reduction, elimination, reuse, or recycling. In this investigation, a multifaceted criterion was used, accounting for the unique and operational constraints experienced by managers and operators in the wine industry. Ranking and screening of waste streams and pollution prevention systems have been extensively discussed by several researchers (Hanlon & Fromm, 1990; Balik & Koraido, 1991; Crittenden & Kolaczkowski, 1995; Smith & Khan, 1995; Allen & Rosselot, 1997). These indices were found to be strongly dependent on the nature of the industry, or problem under consideration, as well as the databases accessible in the domain under study. In this chapter, the Smith and Khan's Index (Smith & Khan, 1995) commonly referred as the pollution prevention index was modified to suit the limitations of the accessible data in the wine industry.

For the purpose of producing a broader and more acceptable prioritization of the derived WM strategies, each strategy was evaluated based on a set of multiple criteria, including the position of a given strategy in the WM hierarchy. Consequently, source reduction was assigned a higher priority in comparison to reuse and recycling. Different criteria were assigned different weights as shown in Table 1. The reason being, each criterion had a different impact on the reduction of the overall quantity of waste generated and the capital costs required for its successful implementation. It should be noted that the Smith and Khan Index (Smith & Khan, 1995) was comprised of source reduction, reuse, and waste treatment in accordance to the EPA pollution prevention hierarchy (USEPA, 1988). However, in this study, the waste treatment, payback period and depth of solution criteria were excluded from the index, owing to waste management challenges unique to the wine industry. The rest of the criteria used in describing WM solutions were recycling, degree of waste reduction expressed in percentage, ease of implementing a given strategy, and the capital cost of a given solution. The weights assigned in each of the criteria were in descending order in accordance with the foregoing description, such that capital cost was assigned the lowest weight of 1, whereas source reduction had the highest weight of 10^5. Note that the percentage of waste reduction was expressed in qualitative terms – and generically was referred as the waste reduction possibility. Thus, the WMI for a given strategy was computed using the relation:

$$WMI = SR \times 10^5 + Re \times 10^4 + R \times 10^3 + WRP \times 10^2 + IP \times 10^1 + CC \times 10^0 \quad (1)$$

where SR: source reduction, Re: Reuse or recovery, R: reclaim or recycle, WRP: waste reduction possibility, IP: implementation potential, and CC: capital cost.

Criteria	Weight	Activity		Index value
Source Reduction (SR)	10^5	Elimination		1.00
		Minimize	High	0.75
			Medium	0.50
			Low	0.25
Reuse/Recovery (Re)	10^4	Full		1.00
		Partial		0.67
		Low		0.33
Reclaim/Recycling (RR)	10^3	Full		1.00
		Partial		0.67
		Low		0.33
Waste Reduction Possibility (WRP)	10^2	No reduction (nr)		0
		Low reduction (lr)		1
		Moderate reduction (mr)		2
		High reduction (hr)		3
Implementation Potential (IP)	10^1	Procedure change (pc)		5
		Material substitution (ms)		4
		Preventive maintenance		3
		Retrofit equipment (re)		2
		New equipment		1
Capital Cost (CC)	10^0	No cost (nc)		5
		Low cot (lc)		4
		Moderate cost (mc)		3
		High cost (hc)		2
		Very high cost (vhc)		1

Table 1. WM index for the wine industry (adapted from the Smith and Khan Pollution Index (Smith & Khan, 1995).

2.3 Qualitative reasoning

The concept of qualitative reasoning (Bobrow, 1984; Kleer & Brown, 1984) was applied to aid in representing and making available general and physical knowledge commonly used by engineers, scientists and managers to address the environmental problems experienced in the wine industry – without invoking mathematics of continuously varying quantities and differential equations. This is because qualitative reasoning provides the most suitable platform to represent numerous qualitative abstractions specific to the wine industry through creation of quantitative models, without the necessity for rigorous mathematical computations. The use of qualitative symbolic representations and discrete quantities aided in modeling the complex behavior of different vinification processes and unit operations. Therefore, the qualitative approach aided in predicting the behavior of processes and unit operations satisfactorily because only a small number of qualitative variables were required to describe the system. As such, the qualitative reasoning was used to describe the qualitative 'states' attainable with or without implementation of a given strategy in order to mitigate against waste generation, or in improving the management of inevitable waste streams.

Consequently, a qualitative model was developed as point of departure without the necessity for detailed information on the implementation of various WM strategies in the winemaking process. For example, consider the WM strategy where a counter current method is applied to reduce the effluent generated during cleaning. Using qualitative reasoning, it is feasible to predict at least three possible 'states' – which satisfies the condition of using a small number of qualitative variables – after the strategy is applied. The states were derived from casual observations, or based on experience from previous measurements where the primary goal was to model the level of the strategy's actual 'effectiveness' after implementation.

The effectiveness of applying a counter current WM strategy in a specific winery was described by three 'states', namely; effective, partially effective, not effective. Therefore, there were three possibilities regarding the final effluent quantity that can be predicted using a qualitative reasoning approach, viz.; high potable water usage (if the strategy is poorly or not implemented), moderate potable water usage (if the strategy is partially implemented), and low potable water usage (if strategy implemented adequately).

Practically, the implementation of a given WM strategy can yield a continuum of possibilities ranging from the best case scenario (adequate implementation) to the worst case scenario (poor or no implementation). To attain such possibility may necessitate an increase on the number of predictable states by the model from three to nine. This has the advantage of broadening and increasing the sensitivity of the solution space of the decision support system. This was achieved by combining the degree of belief, or level of confidence (CF) the user expresses on a particular response regarding the implementation of a given strategy. Three levels of CF values were specified in this work, and were combined through simple algebraic multiplication to the dimensionless scores representing the qualitative values of a given strategy to expand the predictable states from three to nine. If the qualitative values of a given strategy are assigned dimensionless scores, x_{i1}, x_{i2}, x_{i3}, and CF values y_1, y_2, and y_3: then the possible predictable states for a single strategy or action can be modelled by the relation:

$$(x_{i1}, x_{i2}, x_{i1}) \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = (x_{i1}y_1, x_{i1}y_2, x_{i1}y_3, x_{i2}y_1, x_{i2}y_2, x_{i2}y_3, x_{i3}y_1, x_{i3}y_2, x_{i3}y_3) \quad (2)$$

where the CF values were fixed at 1.00, 0.75 and 0.50 for y_1, y_2, and y_3, respectively, and i denotes the strategy under consideration. Note that $x_{i1}y_1$, $x_{i2}y_1$, $x_{i3}y_1$ are equal to the original three predictable states represented by the values x_{i1}, x_{i2}, x_{i3}, correspondingly.

The next task was to determine a suitable methodology of aggregating the quantitative outputs derived using Eq. 2 that influences a given variable, which in turn exerts a direct impact on the magnitude of a specific targeted system output (e.g. effluent quantity). In this study, the aggregation process was based on the following premise. No single strategy could adequately address the WM problem in the wine industry in a given process or unit operation. Hence, several strategies had to be implemented concurrently in an integrated manner in order to address the waste management challenges in the wine industry adequately. Therefore, the variables used as linguistic input values into the fuzzy model were functions of sums of individual strategies influencing it (Section 3). Equally important, to determine the crisp numerical value of a given variable, all scores from strategies influencing it were summed and normalized using a mathematical expression of the form:

$$Var_k = \frac{\sum_{i=1}^{n} F(x_{ni}, y_j)}{Max\left(\sum_{i=1}^{n} F(x_{ni}, y_j)\right)} \times S_m \tag{3}$$

where Var_k is the k^{th} variable, x_{ni} is the dimensionless score assigned to a strategy's qualitative value, y_j is the user's level of confidence to a given response, n is the total number of strategies influencing the k^{th} variable, j= 1, 2, 3 with fixed numerical values of 1.00, 0.75 and 0.50, correspondingly; and S_m is the m^{th} standardization coefficient where its values were 10 for m=1, or 100 for m=2. The aggregation principle applied in this study is schematically represented in Fig. 2.

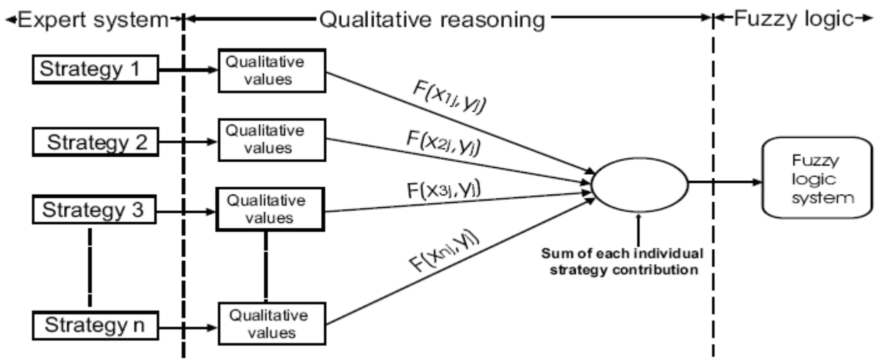


Fig. 2. A conceptual framework based on qualitative reasoning to transform qualitative values into fuzzy numbers.

2.4 Fuzzy logic

The fundamentals of fuzzy set theory (Zadeh, 1965; Yen & Lugari, 1998) are well known (Klier & Yaun, 1988; Zimmermann, 1991; Yager & Zadeh, 1992; Yager & Filev, 1994; Yen & Lugari, 1998; Mamdani & Assilian, 1999). Thus, only the most salient features of fuzzy systems essential for designing and developing an intelligent decision support system are summarized. Fuzzy logic generalizes ordinary or classical sets in an attempt to model and simulate human linguistic reasoning particularly in domains characterized by incomplete, imprecise, vague and uncertain data and knowledge. As such, fuzzy logic being a soft computing tool has the "ability to compute with words", and therefore, provides rational and well reasoned out solutions for complex real world problems (Bonissone, 1997), such as WM in the wine industry (Musee et al., 2004a; Musee, 2004b; Musee et al., Musee et al., 2005; Musee et al., 2006a).

2.4.1 Fuzzy membership functions

In a fuzzy system, the variables are regarded as linguistic variables to aid 'computation with words'. A linguistic value is defined as a variable whose value is a fuzzy number, or is a variable defined in linguistic terms (Lee, 1990). Each linguistic value, LV, is represented by a membership function $\mu_{LV}(x)$. The membership function associates each crisp input, say X_A, with a number, $\mu_{LV}(x_A)$ in the range [0,1]. Essentially $\mu_{LV}(x_A)$ represents the grade of the membership of x_A in LV, or equivalently, the truth value of proposition 'crisp value A is LV'. The overlapping of the membership functions allows an element to belong to more than one set simultaneously, and the degree of membership into each set indicates to what extent the element belongs to that particular fuzzy set (Fig. 3).

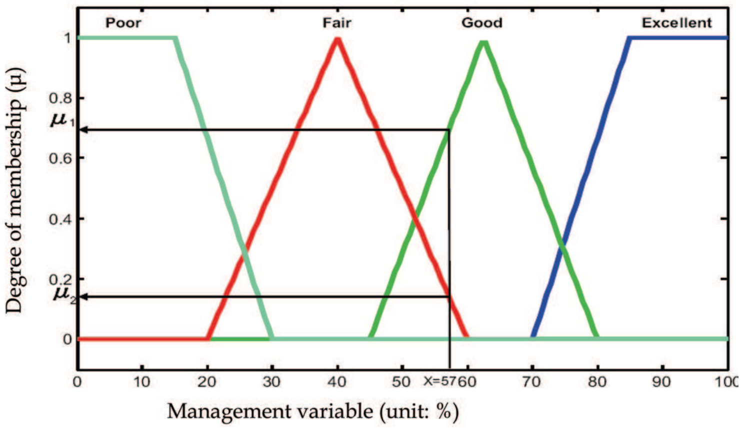


Fig. 3. Triangular and trapezoidal membership functions for the effluent quality management variable with fuzzy linguistic terms: poor, fair, good, and excellent.

To illustrate the functionality of the membership functions for the purpose of determining the linguistic value of a given variable, a simple example is provided. Let the crisp input value for the effluent quality management linguistic variable be x = 57 in a universe of discourse of 0 to 100. Then, according to Fig. 3, an input of 57 generates two membership functions μ_{AC} (x_i), viz. μ_1 = 0.686 in the fuzzy set labelled Good and μ_2 = 0.150 in the set labelled Fair. Note that the rest of linguistic values Poor and Excellent each had a membership function of zero. By applying the max-min fuzzy inferencing algorithm (Lee, 1990) where the membership function values are μ_1 = 0.686 and μ_2 = 0.150, then the linguistic value was determined as Fair (Min [(0.686, 0.150)] =0.150).

2.4.2 Knowledge representation

In a fuzzy rule-based modelling system, knowledge is represented by use of linguistic IF-THEN rules. Ultimately, this renders the knowledge library (base) the core of the system and, the breadth and quality of the knowledge determine the capacity of the system to render useful intelligent decision support. Generically, the premise and conclusion parts of the fuzzy rules are of the form:

$$R^{(l)}\text{: IF } x_1 \text{ is } F_1^1 \text{ AND}\ldots\ x_n \text{ is } F_n^l,$$

$$\text{THEN } y \text{ is } G^l \tag{4}$$

where F^l_i and G^l are fuzzy sets, $x = (x_1, \ldots , x_n)^T \in U$ and $y \in V$ are linguistic input and output variables, respectively, with l = 1, 2, …, M. Practically, the fuzzy IF-THEN rules provide a convenient framework for incorporating human experts' knowledge in fuzzy expert systems. Each fuzzy IF–THEN rule (Eq. 4) defines fuzzy set $F^l_1 \times \ldots \times F^l_n \Rightarrow G^l$ in the product space U × V.

The knowledge necessary for decision making regarding WM in the wine industry was encapsulated in several rule bases with a total of 152 rules. Additionally, the rules were systematically encoded into different hierarchically interlinked rule bases to ensure their easy accessibility at different levels of the decision support execution, and on the other hand, to minimize the overall number of rules in the rule bases. The design of hierarchically interlinked rule bases is analogous to consulting several experts on a certain problem, to derive a final conclusion that takes into account each individual opinion. The model is flexible, robust, and allows the user to choose initial values or adjust the rules in any knowledge base on the basis of operational realities related to the vinification process or processes under scrutiny. Notably, the use of few IF-THEN rules has the merit of aiding in validating the functionality and the contribution of each rule in a given rule base.

2.4.3 Fuzzy inferencing

The core of decision making in a fuzzy logic system is the inference engine. Fuzzy inferencing is used to derive an aggregated output from a particular knowledge base using the rules coded in specific rule bases. In practice, many fuzzy inferencing methods have been developed, with the so-called max-min and max-dot or max-prod (Lee, 1990; Mendel, 1995; Yen & Lugari, 1998) being the most popular. In this case the max-min fuzzy inferencing algorithm proposed by Mamdani & Assilian (1999) was applied. According to the Mamdani-Assilian inferencing algorithm, the truth values of the fuzzy output variables are clipped, such that the area under the clip line determines the outcome of the rule. Finally, a defuzzifier converts the fuzzy aggregate membership grades generated from the inference engine into non-fuzzy output values. Again, there are various approaches to defuzzification (Mazumoto, 1995; Mendel, 1995). The most common is Yager's centroidal method (Yager, 1980), and was applied in this study because of its sensitivity in comparison to other techniques (Yager & Zadeh, 1992).

To illustrate how the fuzzy inference system aided in diagnosing the WM in the industry, a brief description of its salient features and functionalities are presented. Notably, each of the four knowledge sub-modules had a set of features in the form of data, information, and knowledge stored in various interlinked data bases and rule bases as described in Section 3. The hierarchical reasoning structure of each knowledge sub-module can be generically summarized as follows:

1. The linguistic set of strategies/actions were transformed through qualitative reasoning, as well as ranking and screening processes into dimensionless scores at the first hierarchical level (Level-III) of each knowledge sub-module (Fig. 1) using Eqs. 1 and 2.

2. The qualitative or linguistic strategies/actions were broadly grouped into two or three fuzzy linguistic input variables. For example, strategies affecting the effluent quantity were aggregated into three linguistic input variables, viz. organic matter removal, equipment efficiency, and effluent quantity (volume) management. These linguistic variables were used in evaluating the targeted system output (e.g. effluent quantity) at various hierarchical levels of a given knowledge sub-module (see Figs. 2 and 6).
3. The inference for computing the crisp numerical input variable values was performed through solving a series of algebraic summation equations in a specific knowledge sub-module. For instance, to evaluate the degree of product and by-products recovery Eqs. 9 and 10 (in Section 3) were used to compute the fuzzy crisp inputs for the organic material recovery and the general management variables, respectively.
4. The crisp inputs derived in step 3 for a given targeted system output (e.g. chemical usage or effluent quality) were fed automatically into the fuzzy model to derive a final aggregated and ranked output depending on a given set of user's specified inputs. Note that the final fuzzy model crisp output signified a measure of given winery's performance with respect to the targeted system output such as chemical usage, effluent quality, etc.

To illustrate the system's functionality, let's consider the data and knowledge stored for evaluating product and by-products recovery before wet cleaning and sanitization processes. Assume that from steps 1 to 3, the product and by-products recovery (PBR) and generic management crisps values were computed as 0.48 and 55% in their respective domains of discourse. After coding the crisp input values into the fuzzy product and by-products recovery rule base module – resulted in firing four IF-THEN rules in the rule base as shown in Fig. 4. To infer the final system output, first, each of the four activated rules had to be evaluated individually. The linguistic rules and the evaluation findings are as follows:

Rule #10: IF PBR is Moderate AND Generic management is Good
THEN Effective PBR_{eff} is Moderate
EVALUATION: Min (0.30, 0.57) = 0.30

Rule #11: IF PBR is Moderate AND Generic management is Fair
THEN Effective PBR_{eff} is Low
EVALUATION: Min (0.30, 0.25) = 0.25

Rule #14: IF PBR is Low AND Generic management is Good
THEN Effective PBR_{eff} is Low
EVALUATION: Min (0.96, 0.57) = 0.57

Rule #15: IF PMR is Low AND Generic management is Fair
THEN Effective PBR_{eff} is Low
EVALUATION: Min (0.96, 0.25) = 0.25

The fuzzy model through fuzzification process derived the evaluation results as follows. A PBR input of 0.48 produced 0.96 and 0.30 degrees of membership in the fuzzy sets Low and Moderate, respectively. Similarly, a crisp input of 55% for the generic management variable yielded membership degrees of 0.25 and 0.57 in the fuzzy sets Fair and Good, respectively. The clipped membership functions derived from the four activated rules in the rule base

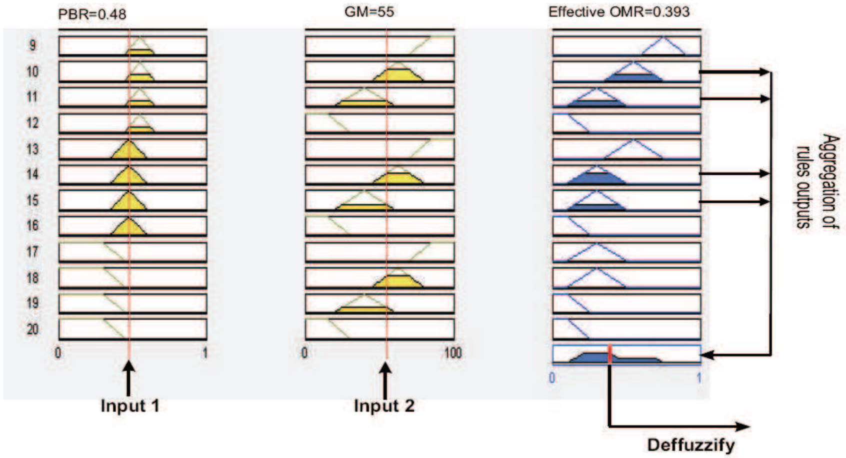


Fig. 4. Fuzzy inferencing mechanism using Mamdani-Assilian model to evaluate the product and by-products recovery (PBR) with two input-variables, and four activated rules.

were aggregated through the defuzzification process into a numerical score (Fig.4). The aggregated system numerical output of the four fuzzy sets signified an overall estimation of the recovered product and by-products, and was determined using the disjunction (max) operator based on the Yager's centroidal defuzzification method given by the expression:

$$Z^* = \frac{\sum_{j=1}^{n} \mu(\omega_j)\dot{\omega}_j}{\sum_{j=1}^{n} \mu(\omega_j)} \tag{5}$$

Applying Eq. 5 on the four fuzzy set outputs yielded a crisp output of 0.393 which was linguistically ranked as Low recovery of product and by-products.

3. Intelligent decision support system development

A systematic methodology for data acquisition as well as knowledge inferencing and manipulation was developed for the purpose of representing diverse findings concerning different aspects of WM in the wine industry. The unique protocol for data handling was essential to ensure that the final findings were transparently computed, hence, could easily be interpreted by the targeted end-users. Generically, the development of an intelligent decision support system comprised of three steps, namely knowledge acquisition, knowledge representation, and inference mechanism. In the following sections, salient aspects on each of the above steps in the context of WM in the wine industry are summarized.

3.1 Knowledge acquisition

Knowledge acquisition entailed the sourcing of data, information and knowledge concerning WM in the wine industry. The knowledge was manually collected through conducting interviews with experts and extensive literature reviews. The knowledge was broadly classified as generic knowledge (GK) or specific knowledge (SK) (Fig. 5). The GK comprised of WM techniques and practices that were universally applicable to a wide range of processes and unit operations owing to their repetitive (routine) character. Conversely, SK focused on WM techniques and strategies for specific process or unit operation, and particularly targeting the intrinsic waste streams (Musee et al., 2007).

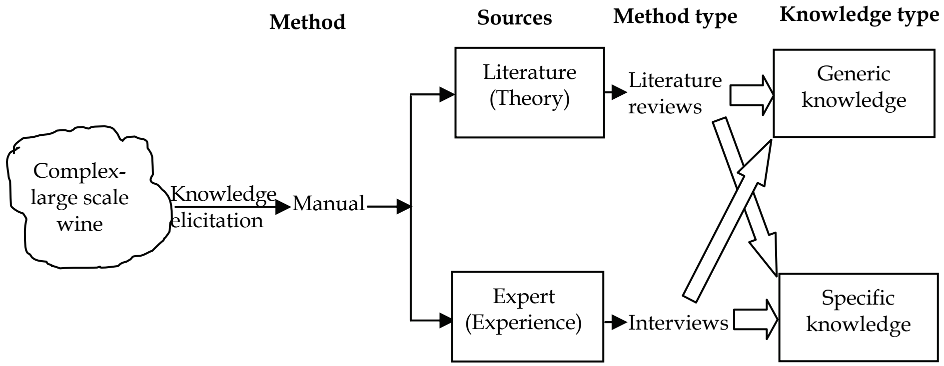


Fig. 5. Data and knowledge sources, knowledge type accessible, and knowledge acquisition for WM in the wine industry.

Equally important, the strategies for either knowledge type (SK or GK) were dependent on the target output under consideration. For instance, the knowledge-type strategies for evaluating the products and by-products recovery were different from those of effluent quality both in the case of intrinsic or extrinsic waste streams. The combining of generic and specific knowledge types and exploitation of the synergies between them lead to the development of rule bases that captured a good degree of WM strategies in the context of the wine industry. Only the knowledge in product and by-products sub-module, as well as effluent quantity sub-module are briefly described in the following sections.

3.1.1 Products and by-products losses/recovery sub-module

Solid wastes from the vinification processes contain commercially valuable products (wine) and by-products. However, depending on the way the solid waste streams are handled, either the products/by-products recovery can be optimized, or huge losses are incurred. The degree of product and by-product recovery is dependent on the vinification processes and unit operations under consideration, or the vinification season (vintage or non-vintage). As a result, the loss of the product and by-products has a direct impact on the final effluent quality and quantity as they resulted into the liquid waste streams – mainly the wastewater.

In order to compute the degree of product and by-products recovery in a given vinification process, strategies related to intrinsic and extrinsic factors, the vintage season, and experts' estimations of relative contribution of the potential losses for each process under scrutiny – were taken into account. Notably, only strategies that had a direct link to recovery, or loss of the products or by-products were taken into account in this sub-module. Experts were asked to provide an estimation of product and by-products overall impact on the quality and quantity of the effluent on a scale of zero to one. An example of heuristics from two experts is presented in Table 2. The values were estimates in relative terms between different processes and unit operations on the basis of a given expert's opinion. During the computation of the final product and by-products the average of values of the six experts who provided inputs were used, for the vintage and non-vintage seasons.

Process/unit operations	Effluent quantity				Effluent quality			
	Vintage		Non-vintage		Vintage		Non-vintage	
	EP1	EP2	EP1	EP2	EP1	EP2	EP1	EP2
Crushing/destemmi	0.10	0.25	0.00	0.00	0.15	0.30	0.00	0.00
Wine transfers	0.25	0.15	0.35	0.25	0.30	0. 10	0.40	0.35
Filtration	0.15	0.10	0.20	0.25	0.10	0.10	0.10	0.15
Pressing	0.20	0.20	0.15	0.15	0.15	0.30	0.10	0.20
Fermentation	0.25	0.25	0.20	0.20	0.25	0.20	0.25	0.15
Bottling/packing	0.05	0.05	0.10	0.15	0.05	0.10	0.15	0.15
Sum of weights	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

Table 2. Two experts' approximation concerning potential losses of product and by-products under different processes and vinification seasons. Note: Values are based on South Africa vinification processes, EP: expert opinion.

An estimation of the quantities of products and by-products recovered during a given season was computed as follows. First, qualitatively the degree to which the generic and specific strategies were implemented in a given facility was evaluated using the qualitative reasoning approach. Secondly, the computed values owing to generic and specific implementation of the strategies were added. The additive value was taken as an indication of the degree to which product and by-products were recovered from surfaces and equipment before wet cleaning and sanitization processes commenced. Thirdly, to ensure uniformity and interpretability of values in a given process or unit operation, and consequently in the entire vinification process, the computed values were normalized. For example, assume for process i, the values obtained after the implementation of the generic and specific strategies are A_i and B_i, respectively. Then, the normalized value N_i for process i is given by the expression:

$$N_i = \frac{A_i + B_i}{A_{it} + B_{it}} \tag{6}$$

where A_{it} and B_{it} are the maximum values if all the generic and specific strategies were adequately implemented in process i.
Thus, the total recovery of products and by-products (PBR) for the entire vinification process is approximated by a linearly weighted expression:

$$PBR = \sum_{i=1}^{6} (N_{is}\beta_i) \tag{7}$$

where PBR is the total recovered product and by-products from all processes and unit operations in season s defined in the range 0 to 1. Zero means no recovery, hence maximum losses whereas one implies maximum recovery of the product and by-products. $ß_i$ is the weight specified by the waste management experts in the wine industry for processes i (i=1, 2, …, 6) during season s (s = 1 (vintage), 2 (non-vintage)) satisfying the condition:

$$\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 = 1 \tag{8}$$

Note that processes i (i = 1, 2, …, 6) represent crushing and destemming, transfer systems, filtration, pressing, fermentation, and bottling and packing processes, respectively. N_{is} is an index in the range ($0 \leq N_{is} \leq 1$) representing the recovered organic material in a specific process i before wet cleaning starts and is computed using the relation:

$$N_{is} = \frac{\sum_{i=1}^{n}(W_{nA} \times CF_k) + \sum_{i=1}^{m}(W_{mB} \times CF_k)}{Max\left(\sum_{i=1}^{n}(W_{nA} \times CF_k) + \sum_{i=1}^{m}(W_{mB} \times CF_k)\right)} \tag{9}$$

where W is the dimensionless score assigned to the qualitative values of each strategy; A symbolizes specific strategies; B symbolizes generic strategies; n is the number of specific strategies considered in process i; and m is the number of generic strategies considered to improve product and by-products recovery in all processes and unit operations under consideration; CF_k is a measure of the degree of belief the user has on a given response regarding a particular practice or strategy; k = 1; 2; 3 whose values were fixed at 1.00, 0.75, and 0.50, respectively.

A schematic representation of computations for ranking the product and by-products recovery in a given season is shown in Fig. 6. The generic and specific knowledge derived for the product and by-products recovery sub-module are presented in Tables 3 and 4, respectively. The second variable that exerted influence on the product and by-products recovery is the generic management (GM_{PBR}). This variable was determined by qualitatively evaluating the last four strategies in Table 3. GM_{PBR} was evaluated and normalized using the expression:

$$GM_{PBR} = \frac{\sum_{i=1}^{q}(W_{qC} \times CF_k)}{Max\left(\sum_{i=1}^{q}(W_{qC} \times CF_k)\right)} \times 100 \tag{10}$$

GM_{PBR} was defined in the discourse of 0 to 100. The value 0 represents the worst management scenario, while 100 imply the best management attainable in a specific facility.

In real plant practices, overall effective product and by-products recovery is a function of PBR (operating and technological solutions) and GM_{PBR} (management-related aspects) variables. Since both variables contain uncertainty (vagueness) and are linguistically quantified, the overall effective product and by-products recovery was evaluated using the fuzzy mathematical formalism of the form:

$$PBR_{eff} = f\left(PBR, GM_{PBR}\right) \tag{11}$$

where f is a fuzzy logic function, PBR_{eff} is defined in the range 0 to 1, such that 0 represents a scenario where no recovery of product and by-products takes place before wet cleaning occurs while 1 signifies the best case scenario representing optimal recovery of product and by-products.

Influencing factors	Qualitative levels of action	WMI[a]	Rank[b]
Prevention/and or reduction of products and byproducts dispersion.	Effective Fair Low	100,451	2
Institutionalization of process procedures for waste dispersion elimination/ and dispersion.	High Moderate Low	100,355	3
Percentage of waste streams segregation.	High (65-100%) Moderate (40-65%) Low (below 40%)	75,292	4
Frequency of spillages, leakages, incidentals and accidents during the operations.	High (70-100%) Medium(30-70%) Low (under 30%)	50,313	6
Levels of progressive prioritization of education on waste management in a winery at the following personnel:			
Senior management.	High Medium Low		
Skilled workers.	High Medium Low		1[c]
Unskilled workers.	High Medium Low		
Levels maintenance of facilities and equipment.	Routinely done Often done irregulary/not done	75,241	5
Time laspe between end of a process or operation and commencement of products and byproducts recovery.	Immediately After sometime After long time	25,155	7

Table 3. The rankings of the generic strategies influencing the recovery and handling of product and by-products for intrinsic wastes[1].

3.1.2 Effluent quantity (volume) sub-module

Fig. 7 depicts a hierarchical model for evaluating the effluent quantity generated during the cleaning and sanitization processes in a winery. The aggregated effluent quantity is a function of three linguistic variables, namely: the organic matter removal (OMR_s), equipment efficiency (EE_v), and effluent quantity (volume) management (M_v). The strategies influencing effluent management are summarised in Table 5. The effluent quantity management variable (M_v) is a function of generic effluent quantity management (M_{gv}) and the generic management of product and by-products (GM_{PBR}) variable at Level-II as depicted in Fig. 7.

[1] [a]WMI: waste minimization index discussed in section 2.2; [b]Ranking was used to facilitate the process of assigning dimensionless scores to aid in the evaluation of the degree to which product and by-products were recovered from a given process or unit operation. [c]The extent to which various strategies were effectively implemented in a winery for minimizing or eliminating waste as function of training and awareness of personnel at all levels. The training and education factor was ranked as the most significant in this category based on expertise knowledge.

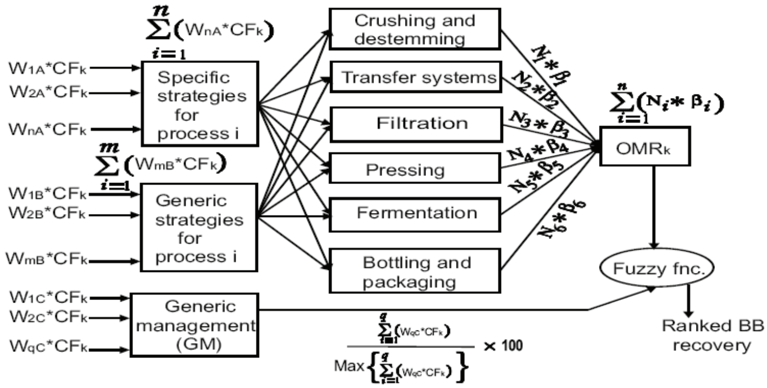


Fig. 6. Hierarchical structure for evaluating overall product and by-products recovery.

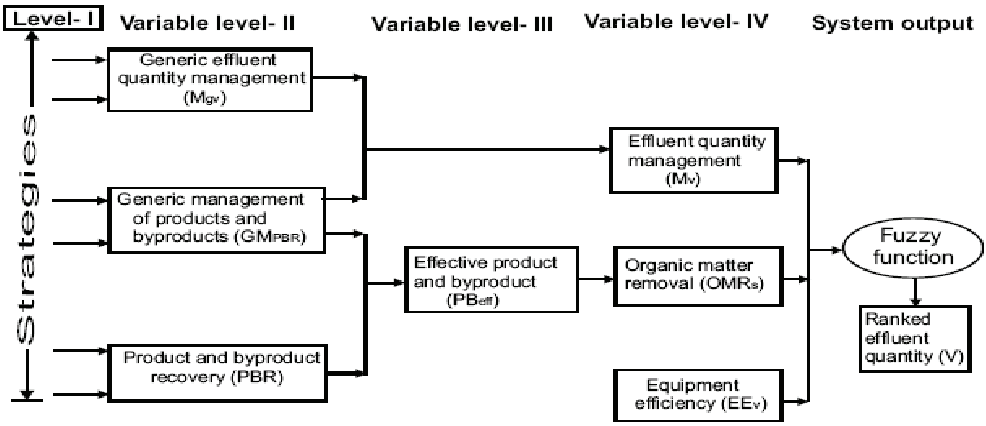


Fig. 7. Hierarchical model structure to evaluate the effluent quantity during the cleaning and sanitization processes.

Note that the crisp numerical value for the generic effluent quantity management, (M_{gv}), is defined as:

$$M_{gv} = \frac{\sum_{i=1}^{n}(W'_{ns} \times CF_k)}{Max\left(\sum_{i=1}^{ns}(W'_{ns} \times CF_k)\right)} \times 100 \tag{12}$$

M_{gv} is defined in the range 0 to 100. 0 implies the worst management scenario whereas 100 signifies the best effluent quantity management achievable in a given winery; W'_{ns} is a dimensionless score for the ith strategy, i= 1; 2; 3; … n in season s.
The generic management of product and by-products (GM_{PBR}) is computed using Eq. 10. Therefore, the effective effluent quantity management linguistic variable, M_v, is defined by the relation;

Influencing factors	Qualitative levels of action	WMI[a]	Ra
1. Crushing and destemming			
Condition of grapes at the time of delivery.	Low quality		
	Moderate quality	100,334	2
	High quality		
Temperature of grapes at the time of delivery.	Low temp.(T $\leq$ 20°C)		
	High temp.(20< T <30)	50,253	4
	Very high temp.(T $\geq$ 30)		
Frequency of dedicating lines of destemming and crushing on the basis of different cultivars.	High		
	Moderate	100,355	1
	Low/low		
Gauge level of site communication during the unloading of grapes.	Highly effective		
	Moderately	100,355	1
	Poorly coordinated		
Effectiveness in terms of grapes delivery to reduce start-up and shut-up wastes.	Continous delivery		
	< 30 min. lag	50,255	3
	> 30 min. lag		
2. Piping and transfer systems			
Percentage approximation of pipes inclined horizontally to enhance products and byproducts flow.	Low/none		
	Medium	50,221	3
	High		
Estimate the overall piping line distances in your facility.	None/very short		
	Moderate to long	25,362	4
	Very long lines		
Extend use of pneumatic/mechanical systems for recovery of products and byproducts in piping and transfer systems.	Extensively used		
	Often used	67,212	2
	Routinely done		
Nature of pipe joints (nature of joints determines the possibility of using pigging techniques for recovery of products and byproducts).	Screwed connect.		
	Screwed and welded	67,282	1
	Welded connection.		
3. Filtration process			
Level of effectiveness of separation process of wine and constituent solids.	Very effective		
	Moderately effective	75,355	2
	Not effective		
Estimated efficiency of handling fitration cakes/filtrates during and after the process.	High		
	Moderate	67,363	4
	Released on floor		
Reuse of filter cakes in the next cycle of filtration or use of virgin materials every cycle.	Often reuse		
	Very limited reuse	67,354	3
	No reuse		
Use of alternative filtration techniques such as centrifuges and optimal capture in place of diatomaceous earth.	Effectively used		
	Often used	100,255	1
	Not used at all		

Table 4. continued …