# Application of Evidence Theory to Automate the Process of Removing Toxic Chromium Ions in Wastewater

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A new method to automate the batch process of removing toxic chromium ions from wastewater using Dempster–Shafer's (DS) evidence theory is described. The removal of the toxic chromium ions from wastewater is a good example of a process where conventional output or state feedback controllers cannot be simply applied because the concentration of the ion cannot be easily measured online or estimated from other measured parameters. The batch process of removing toxic chromium ions by adding a reducing agent involves reduction and oxidation (redox) reactions which are usually monitored using the oxidation reduction potential (ORP) probe. However, the relationship between ORP and concentration of chromium ions is difficult to establish, hence, a reliable online control is seldom achieved using output feedback control. The approach here is to treat the sequence of ORP values obtained at each sample interval as partial evidences with different degrees of belief to indicate whether the removal process has been completed or not. Using DS's theory of evidence these partial evidences are fused or aggregated to give a more reliable and robust real time control decision. In this paper, a modification is proposed to overcome deficiencies in the DS's combination rule in combining sequences of evidence from the same source. The algorithm based on this evidence theory has been tested in the laboratory, and the results obtained show that the algorithm is robust with respect to noise and process variation.

***Keywords:*** Chromium removal process, Dempster–Shafer's evidence theory, evidence aggregation, information fusion, *and* oxygen reduction potential (CRP).

## INTRODUCTION

Typically, in wastewater where toxic hexavalent chromium ions are present, it is essential that the hexavalent chromium ions are reduced to the less harmful and insoluble trivalent chromium ions by dosing with a reducing agent. Subsequently, the trivalent ions will be precipitated as hydroxides so that the precipitates can be filtered out from the bulk treated wastewater. The problem posed in controlling the reduction process is that chromium ions cannot be easily measured online. Oxidation reduction potential (ORP) is widely used as a control parameter in wastewater treatment systems, especially in physicochemical treatment. Some have favored process control based on the absolute value of ORP, while others have preferred control strategies based on relative changes in ORP with time (Wareham et al. 1993). In the former control strategy, the set-point control is used where dosing is stopped when the ORP values reached certain preset limit. The deficiency associated with such method is that ORP values are affected by other redox systems, ionic strengths of various inorganic salts, polarization of electrodes, organic compounds, and temperature effects on electrodes (Campbell et al. 1978) which may vary from one batch to another. For this reason, using a preset ORP limit to trigger off the dosing pump can either lead to incomplete reduction of the hexavalent chromium, or to overdosing.

With the view of developing a more robust method for controlling this reduction process, this paper concentrates on the feasibility of the latter approach using relative change in ORP that has not yet been developed in treatment process of wastewater containing chromium. The latter approach recognizes a general pattern of ORP-time profiles with certain distinctive features, such as the existence of breakpoints, which can be correlated with the disappearance of $Cr^{6+}$. These findings will enable a real-time control of ORP in order to optimize the consumption of reducing agent in the process. This would significantly reduce the operational cost of the treatment process as chemical cost is the main expenditure in physicochemical treatment.

Theoretically, breakpoints can be recognized using short term pattern, but practical consideration such as measurement and process noise made this approach unreliable. For this reason, decision based on long term trend is preferred. The long term trend for this reduction process can be divided into several stages, starting from the initial stage prior to dosing and up to the final stage when the reaction is completed. The pump will be stopped when the last stage is reached. The reliability of the control decision depends on the ability to accurately recognize these stages based on the ORP measurements, specifically, their derivatives calculated using backward difference. However control decision based directly on these derivatives will not be robust as it will be very sensitive to the presence of process and measurement noises, and variation in the process characteristic from one batch to another. The approach taken here is to treat these derivatives as partial evidences to support the belief that the process is in a particular stage. As in any other evidences that we may encounter in our daily lives, evidences are rarely perfect or totally convincing. For any evidence, we can assign a degree of certainty or belief that this particular evidence will correctly point to the right hypothesis.

In this paper, the evidences in the form of crisp backward differences of the ORPs at each sample time are converted into partial beliefs. This conversion can be conveniently done using fuzzy membership function. This assignment of the degree of belief is different from the assignment of the membership grades in the fuzzy sets. Membership grades tell us the degree of membership of a particular crisp attribute to fuzzy sets with unsharp boundaries. In the case of the evidence, the set of decisions to be made are very clear, and the uncertainty is in the reliability of the evidence. These evidences are then aggregated using DS's combination rule to achieve a more accurate and robust decision on the current stage of the process. A modification to this combination rule is proposed here to make it more suitable to combine sequences of evidences gathered over time from the same source. The proposed algorithm has been successfully implemented using a laboratory scale model to automate the process of removing toxic hexavalent chromium in the waste water.

This paper is organized as follows: The section on "Evidence Theory" gives an overview of the theory, in particular, of DS's combination rule. The modification to the DS combination rule for gathering evidence over time is described in "Chromium reduction process." "Proposed Algorithm" describes the approach taken to automate the reduction process using evidence theory. The experimental setup and the results are given in the two following sections before the conclusions.

## EVIDENCE THEORY

Making decisions, whether consciously or not, is part of daily routines. When there are decisions to be made, it implies that there are more than one choice. The choice that was made is based either on clear facts, or more often based on uncertain information. The focus here is on the management of this uncertain information. A number of approaches to manage this uncertainty have been developed. Among these are the Bayesian theory and DS's evidence theory (Mahler 1996, Safer 1976). The main difference between the Bayesian and evidence theories is that, in evidence theory, ignorance is taken into account. Hence, the degree to which an evidence fails to support a hypothesis does not necessarily mean the support for the negation of the hypothesis. In this paper the DS's evidence theory is adopted because of its flexibility in handling ignorance of the source and ease of use. Evidence theory is widely used for sensors fusion (Goodridge 1994, Maurius et al. 2000, Qingdong et al. 2000, Russo 1994, Tong et al. 2000, Wu et al. 1996, van der Wal and Shao 2000), monitoring and fault diagnostic (Loskiewicz-Buczak and Uhrig 1993, Qingdong et al. 2000), image and signal classification (Belloir and Billat 2000, Chao et al. 1996, Gumustekin and Hall 1996, Mirhosseini et al. 1998, Murphy 1996, Tahani and Keller 1990, Verikas et al. 2000). Despite the wide applications, we have not come across any reported work on application evidence theory for real time control purposes. The popular approach in control applications is to use Mamdani fuzzy system (King and Mamdani 1977, Klir and Yuan 1995), however, in the application considered here, fuzzy logic control using Mamdani fuzzy system cannot be used as the controller requires crisp data on the process output which is not available here. Yager (1995) combined DS's theory and fuzzy logic controller, where DS's theory is used to aggregate the consequence so that randomness can be taken into consideration. However, it is still an output feedback controller where crisp output of the process is still required.

### *Belief and plausibility measures*

Let $\Omega$ be a finite universal set with certain attribute, and $\Psi$ be a non-empty subsets of $\Omega$. The set $\Psi$ is called the frame of discernment which contain exclusive and exhaustive possibilities. A mass function ($m$) or basic probability assignment (bpa) is a mapping $m: \Psi \rightarrow [0, 1]$ such that $m(\phi)=0$ and $\sum_{A\in\Psi} m(A)=1$. The value $m(A)$ is interpreted as a measure of belief to which the evidence supports the hypothesis that a particular element belongs to exactly set $A$.

### *Information fusion or aggregation of evidence*

In many applications, partial or uncertain information are collected using several independent sources (such as "sensors') and this information need to be integrated in order to improve the reliability of the decision-making process. The key issue in the evidence theory is how various evidences/information are combined to reduce the ambiguity.

### *Dempster-Shafer evidence theory*

DS's combination rule or orthogonal sum is widely used to aggregate evidences. One of the main advantage of this combination rule compared to the Bayesian method is that prior probability density function is not required. The mass functions $m_1$ and $m_2$ of evidences from two different sources can be combined to obtain a joint basic assignment $m_{1,2}$ using DS's rule of combination:

$$m_{1,2}(A) = \begin{cases} \dfrac{\sum_{B\cap C=A} m_1(B)\otimes m_2(C)}{1-K}, & A\neq\phi \\ 0, & A=\phi \end{cases} \tag{1}$$

where:

$$K = \sum_{B\cap C=\phi} m_1(B)\otimes m_2(C) \tag{2}$$

At this stage, the symbol represents the normal multiplication operator, but later it will be redefined to perform a different operation. $K$ can be seen as a measure of conflict or inconsistency between the sources of evidence. The combination operation is both associative and commutative.

There are many alternatives and variants to DS's rule which have been advocated to overcome certain weaknesses in the rule and to reduce the sensitivity to perturbation in the belief level. Averaging the belief in the combination rule to handle conflicting evidences was proposed in (Hau and Kashyap 1989, Murphy 1999, Pal and Ghosh 2001). Modifications were also proposed to reduce the computational load (Chao et al. 1996, Hong 1992). In order to have more rigorous mathematical basis (Wang et al. 1996) combined the Bayesian theory and the DS's theory. To take into consideration of fact that certain sources may be more reliable than others, the reliability of various sensors is taken into account in the rule proposed by (Tong et al. 2000). While it is true that these modifications will improve the combination rules for certain domain of applications, these modifications are not adopted in the algorithm proposed here as many of these weaknesses are not that significance in the application discussed in this paper. The concern here is on the suitability of using DS's combination rule for combining sequences of evidences from the same source.

### *Aggregation of sequences of evidence from the same source*

There were some concerns raised by Murphy (1996) on the usage of DS's combination rule for combining information gathered from the same sensor over time. The first concern is on the assumption in the DS's combination rule that the measurements are independent, which is certainly not valid here as the same sensor is used. Second, rule of combination is commutative, i.e order is not important. Violation of the first assumption can either lead to result that is counter-intuitive or still acceptable, depending on the applications. Murphy (1996) gave an example on robotic vision where a robot observes an object with 0.6 belief that the object is the target, and 0.4 belief that it is not. If the robot and the object were moving perfectly together, the view, hence the belief levels will remain the same when the next image is captured. Murphy argued that intuitively by repeating looking at the same image, the belief level should not increase significantly. However, DS's combination rule will result in increasing belief level. Murphy (1996) also proposed a modification to the DS's rule by introducing a tuning parameter that will change the characteristic of the combination rule from optimistic (the original DS's rule) to neutral and pessimistic. For the intended application here, although the assumption of independent sources is violated, the pessimistic characteristic of the original DS's rule actually bring unintentional advantage that will make the algorithm more adaptive to the variation in the process characteristics. In order to translate the crisp data into partial belief, the mass function is defined based on the typical process characteristic. If the actual process characteristic is different from the typical characteristic, evidence with high belief level may be assigned a low belief level. Using DS's rule, if the evidences over time are consistent, the aggregated belief level will increase. This behavior closely emulates how human make decision by observing uncertain information gathered over a period of time. If we were presented with evidence that was initially hard to belief, but if similar consistent evidences from the unbias source were presented to us several times, our belief level will gradually increase.

The second concern raised by Murphy (1996) on the commutativity of the evidences gathered at separate time is very relevant to our algorithm. Given that the process that we are monitoring is dynamic, clearly more recent evidence should be more reliable in indicating the current state of the process compared to the previous evidences. Murphy (1996) proposed that the multiplicative term in the operator $\otimes$ in Eq. (1) be replaced such that,

$$m_1 \otimes m_2 = (m_1 * m_2)^n \qquad (3)$$

where, * denote the usual multiplication operator and $0 \leq n \leq 1$. This modification, however, still makes the combination rule in Eq. (1) commutative, meaning it will not recognize that new evidence is more credible than the previous evidence. In this paper, a method is proposed that will reduce the credibility of the evidence prior to combination with the new evidence. Before this modification is described, the interpretation of the mass function from information theory (Carlson 1975) view point will first be reviewed.

Let consider a simple frame of discernment that contains the hypotheses $\{A, \Psi\}$ with mass functions $m(A), m(\Psi)$ assigned to them respectively. In information theory, entropy is used as a measure of the information content. Using the same concept, the entropy or amount of information contains in the evidence from a particular source can be defined as:

$$E = \sum_{X=A,\Psi} m(X)\log_2 m(X) \tag{4}$$

Taking derivative of $E$ with respect to $A$ and given that $m(\Psi)=1-m(A)$, it can be shown that $E$ will be minimized when $m(A)=m(\Psi)=0.5$. This result should be obvious as there is very little information that can be gained from a source that is completely not sure of the hypothesis. This result also carries to DS's combination rule with simple mass functions. Let $m_1(A)$ and and $m_2(A)$ denote the belief levels for hypothesis $A$ based on evidences from the first and second sources respectively. If $m_2(A)=0.5$, then it can be easily shown that the combined evidence $m_{12}(A)=m_1(A) \oplus m_2(A) = m_1(A)$, i.e the evidence from the second source neither reinforce nor degrade the initial evidence provided by the first source. Thus, it can be seen that the information content of the evidence is less if the belief level is close to 0.5. Therefore, the evidence can be devalued by adjusting its belief level closer to 0.5. Let $m$ denote the raw evidence. The devalued evidence of $m$ is defined as:

$$m^{\alpha} = \alpha\, m + 0.5(1-\alpha) \tag{5}$$

where $\alpha$ is the devaluation factor and $0 \le \alpha \le 1$. $\alpha = 1$ corresponds to no devaluation in the evidence, and $\alpha = 0$ signifies that the evidence should be ignored as it carries no value. This method can be used to give relative importance to different evidences gathered at different times. In this paper, two combination rules are proposed to combine sequences of evidence obtained at different times: the *Fixed Window Length* and *Recursive* methods.

### Fixed window length combination method

The method can be described as follows:

**Step 1:** Let $m_{k-1}$ and $m_k$ denote the mass function for the evidence obtained at $(k-1)^{th}$ and $k^{th}$ time steps. Prior to combination using DS's rule, compute the devalued evidence for $m_{k-1}$ using Eq. (5):

$$m_{k-1}^{\alpha} = \alpha\, m_{k-1} + 0.5(1-\alpha) \tag{6}$$

**Step 2:** Combine $m_{k-1}^{\alpha}$ with $m_k$ using DS's combination rule to obtain the accumulated evidence $m_{k-1,k}$:

$$m_{k-1,k} = m_{k-1}^{\alpha} \otimes m_k \tag{7}$$

Eq. (7) describes the combination rule for window length of 2. The above rule can be extended to a window of any length $N$. Let $m_k^{k-N}$ denote the combination of the evidences from time $(k-N)^{th}$ to $k^{th}$ time steps. The time

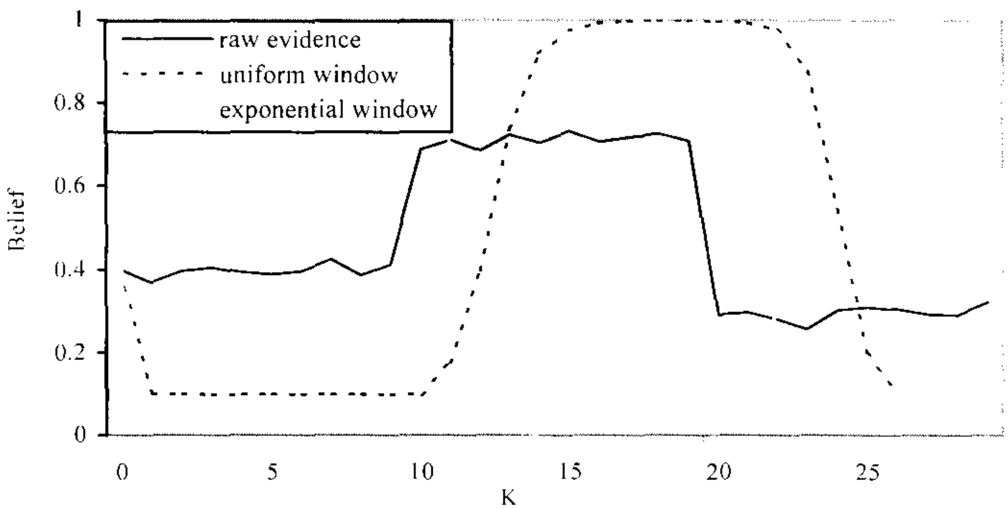


***Figure 1. Aggregation Using Fixed Window Length***

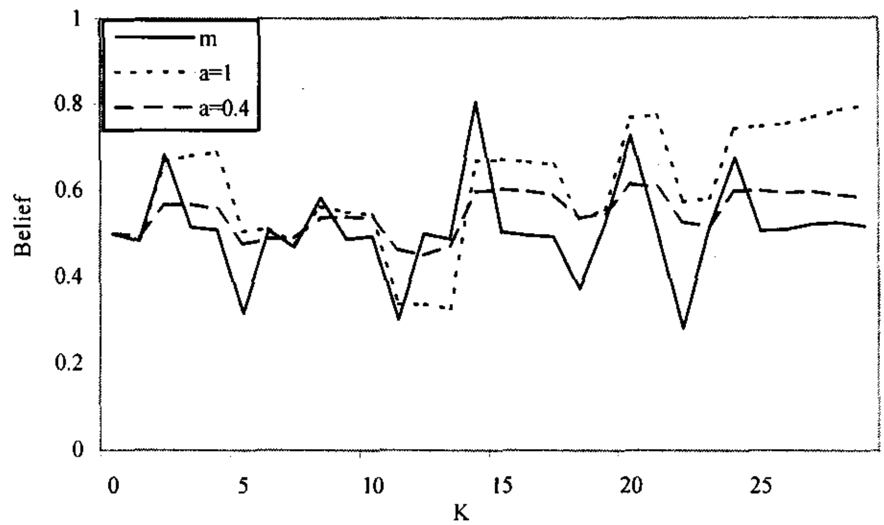


***Figure 2. Recursive Combination Aggregation***

weighted combination of the evidences from time $(k\text{-}N)^{th}$ to $k^{th}$ time steps can be computed using the following equation:

$$m_k^{k-N} = m_{k-N}^{\alpha_{k-N}} \otimes m_{k-N+1}^{\alpha_{k-N+1}} \otimes \quad \cdots \quad \cdots \otimes m_k^{\alpha_k} \quad (8)$$

where, $0 \le \alpha_{k-N} \le \alpha_{k-N+1} \le \ldots\ldots \le \alpha_k \le 1$.

***Example 1.*** This example demonstrates the effect the devaluation factor on the combinations of sequences of evidences. Consider a sequence of evidences as shown in Figure 1. The aggregated beliefs using DS's combination rule with window length of $N=10$ and uniform weights are also shown. This example clearly shows that the DS's combination rule without any modification is very sluggish to response to new evidences. To make the aggregated beliefs more adaptive to new evidences presented, the past evidences can be devalued exponentially in time, i.e the devaluation factor $a=e^{-0.1k}$, where $k$ is the number of past time steps. The improvement in using this time-dependence devaluation factor can be seen in Figure 1.

### *Recursive combination method*

This combination method can be used to reduce the computational burden using fixed window length. Using this method, for a given initial belief $m_{0,0}$ the accumulated belief is:

$$m_{0,k} = m_{0,k-1} \otimes m_k \quad (9)$$

The weakness in the recursive combination in Eq. (9) is that this method gives equal weight to all the past accumulated belief ($m_{0,k}$) and a single new belief ($m_k$). Such combination will make the accumulated belief very sensitive to the "noise" in the new evidence as there is no averaging effect. To overcome such problem the following recursive combination method that exhibits a "low pass filter" characteristic is proposed:

$$m_{0,k} = m_{0,k-1} \otimes m_k^{\alpha} \quad (10)$$

where, $m_k^{\alpha} = \alpha m + 0.5(1-\alpha)$. The following example will show how the devaluation parameter, a affect the result of combining sequences of evidences.

***Example 2.*** Consider the case of the evidences shown in Figure 2 where the belief levels are on average constant except at several instances the belief levels are disturbed by some inaccurate evidences. Figure 2 also shows the aggregated belief using $\alpha = 1$ and 0.4. Results clearly show that with $\alpha = 1$, the aggregated beliefs are very sensitive to disturbances. The filtering effect of using smaller value of $\alpha$ was clearly demonstrated in this example.

## CHROMIUM REDUCTION PROCESS

Figure 3 shows a typical plot of ORP with and without the presence of other metal ions such as $Pb^{2+}$, $Zn^{2+}$, $Ni^{2+}$, and $Cu^{2+}$ (Rozaimah 1999), when a reducing agent, ferrous sulphate, is added at constant rate to wastewater containing $Cr^{6+}$ ions. From the observation of the color changes and confirmed by off-line analysis of $Cr^{6+}$ concentrations using a standard *1,5-Diphenylcarbohydrazide* calorimetrically method at a wavelength of 540 nm via HACH DR/2000 Model 44800-00 spectrophotometer, the reduction process was completed at about 44 seconds (22 time steps) when ORP reached its maximum value before going down due to excess or unreacted reducing agent. Similar trends were also observed when the different initial concentrations of $Cr^{6+}$ or concentrations of ferrous sulphate were used. The analytical method in analyzing the hexavalent chromium ions was performed at the end of each run and had detected no existence of the ions, proving that all hexavelent ions had been reduced to trivalent ions.

Based on this figure it is clear that the ORP reading reached a peak value around 310 mV. Unfortunately, this target value varies as it is dependent on the presence of other redox systems, ionic strengths of various inorganic salts, polarization of electrodes and temperature effects on electrodes (Campbell et al. 1978). Due to this variation the commonly used set-point control such as PID or on-off control based on preset level cannot be used to control the pump for the reducing agent. In the absence of better alternative control strategies, set-point control using relay switching have been used in industries, where typical or average value for the set-points was used. This, inevitably, in most cases leads to either incomplete reduction or wastage of the reducing agent. Control decision based on slope detection to determine the maximum location is another possible method. Slope computation using direct differentiation (backward difference) is very sensitive to process and measurement noise. A more robust method using Kalman filter to indirectly compute the slope was proposed by Crisafulli and Medhurst (1993). Although this method was proven to be successful in controlling this reduction process (Mustafa et al. 2002), it is based on mathematical theory which not many practicing engineers are comfortable or familiar with. Control using neural networks was reported by Rozaimah (1999), but results show performance is not robust due to variation in waste water characteristics from one batch to another.

## PROPOSED ALGORITHM

### *Mass function*

While there is very little doubt on the accuracy of the actual value of ORP, there is a significant

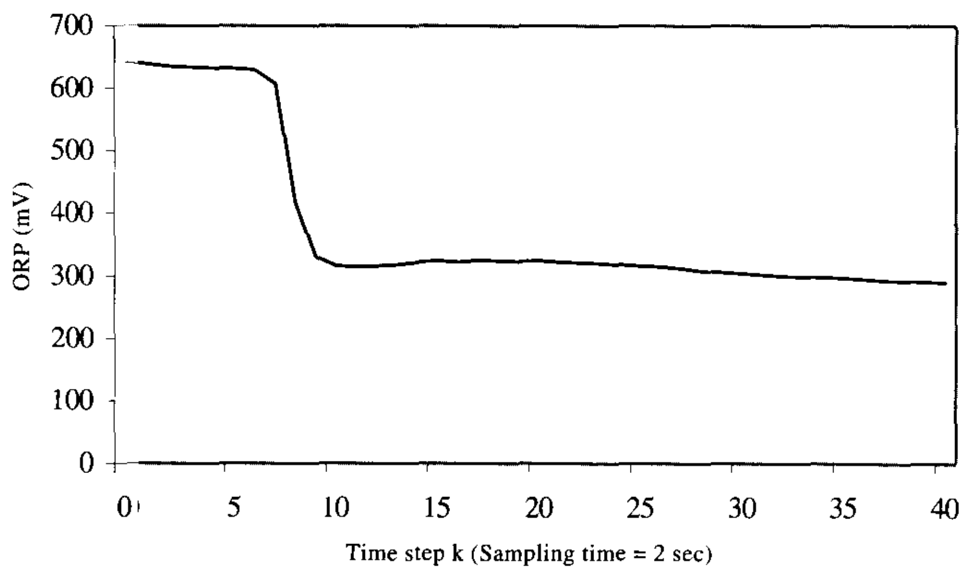


***Figure 3. A Typical Profile of ORP***

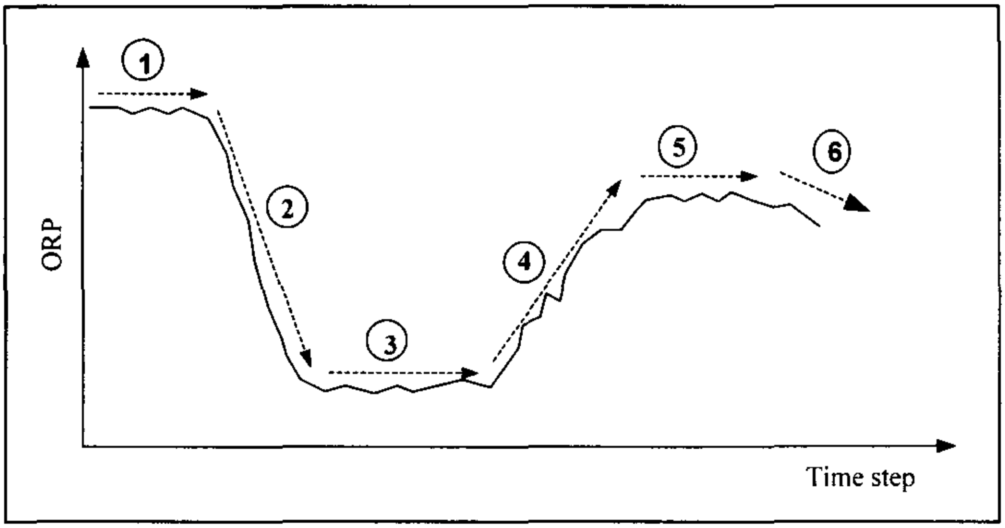


***Figure 4. Stages of the Chromium Reduction Reaction***

uncertainty to decide on the current stage of the process based on this single value. In this paper the usual membership functions (mbf) used in fuzzy logic control shall be used to convert the crisp backward difference in the ORP signals into partial belief. The output of the mbf which lies between 0 and 1 can be directly used as in the DS combination rule. By converting the crisp information into partial belief, the sensitivity problem due to noise and process variation if we were to classify these evidences to either true or false has been reduced. Although mathematically the membership function and mass function are similar, but how they are utilized and interpreted are different in evidence theory and fuzzy logic.

### *Finite state machine and state transition using aggregated evidence*

The development of fuzzy evidence-based algorithm to control the chromium reduction process will be described based on the plot of the output shown in Figure 4. The profile shown here is similar to the one obtained in the experimental application that will be discussed later. The progress of the process shown in Figure 4 can roughly be divided into 5 stages as indicated in the same figure. The number of stage can be reduced by initializing the state machine straight to stage 2 when the pump is started. However, to give a more complete picture of the process, monitoring started from stage 1. The idea behind the proposed algorithm is to automatically track the progress of the process by mapping this sequence of stages onto the states of finite state machine (FSM), and associating the controller output with each state. In this case the controller output will be to keep the pump running until stage 6 is reached.

Each backward difference of ORP reading conveys evidence about a particular stage and this evidence is translated into partial belief that process is in any particular stages. Take for example, with process is in the initial stage 1, the ORP readings will almost immediately decrease when the dosing pump is turn on. However, it cannot be concluded that any detected decrease in the ORP readings as indication that the process is in stage 2 because this decrease in the readings may be attributed to measurement or process noises. To enable robust decision to be made, these evidences will be aggregated over time, and decision on whether the state remains at state 1 or progress to state 2 will be based on the stage which accumulate the higher score. The desired sequence of stage that the controller should evolve is that starting in stage 1, as new evidence (fuzzified backward difference of ORP) comes in, the belief level for the hypothesis that the process is in stage 1 will be reduced and belief level for stage 2 will increase. Then the belief level will gradually shifted to stage 3, and, this will continue until stage 6 is reached. The completion of the reaction is recognized when the last stage (stage 6) is reached. Figure 5 shows graphically an example of how this gradual transition in the belief level of belonging to any stage takes place.

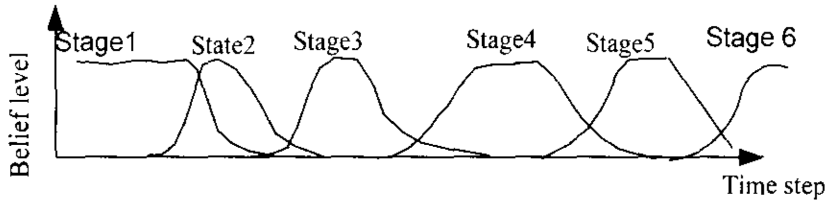


*Figure 5. Accumulated Belief for Various Process Stages*

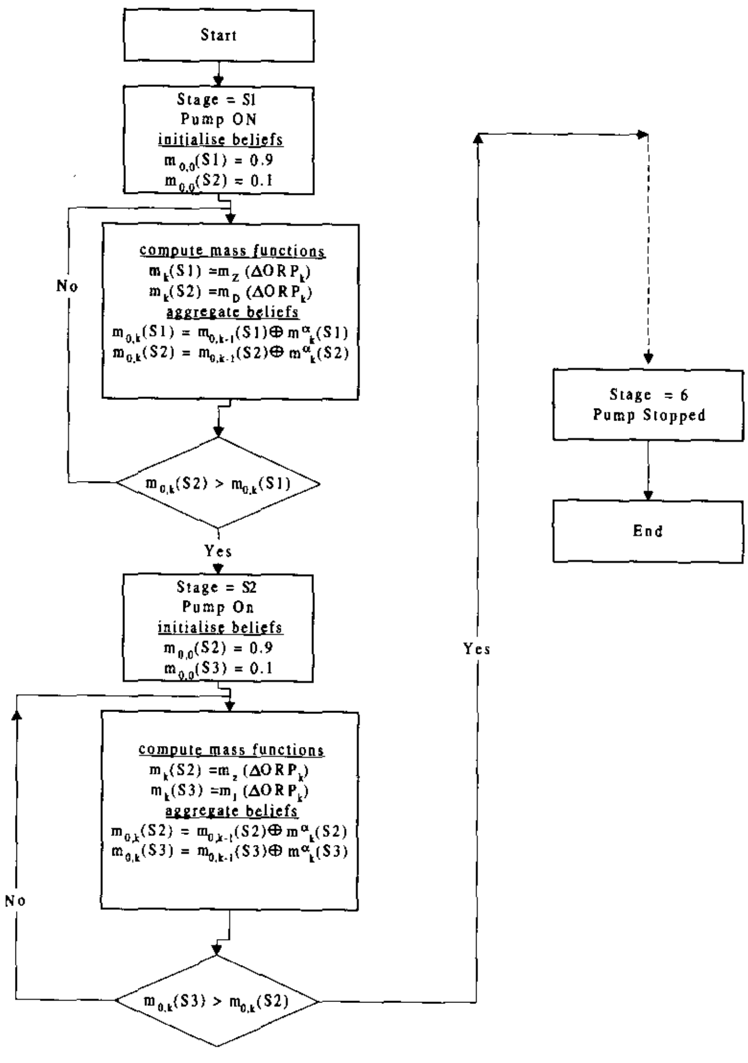


*Figure 6. Algorithm to Determine the Process Stage*

The flowchart for the proposed algorithm to determine the stage of the process is shown in Figure 6. Few minor modifications need to be done to this algorithm to handle certain "difficult" conditions. These modifications will be discussed later in the result section. It can be seen from Figure 6 that at any time, the frame of discernment is $\psi$ = {Remain at present state, Move to next state}. By breaking and tracking the progress of the reaction the number of hypothesis in the frame has been reduced to two. If the decision on the stage of the reaction is based on the instantaneous trend, the number of the hypothesis will be the same number as the stages. The reduction in the number of stage simplifies the computational task and more robust to noise or short term disturbances in the process.

The functions $\mu(.)$ in Figure 6 are the membership functions to convert the crisp backward difference of *ORP* ($\Delta ORP_k$) into mass functions. By referring to Figure 3, the functions $\mu_Z(\Delta ORP_k)$, $\mu_D(\Delta ORP_k)$, and $\mu_I(\Delta ORP_k)$ are membership functions that provide the evidence for the hypothesis that the process is in a particular stage. The subscripts *Z, D,* and *I* stand for *Zero, Decreasing*, and *Increasing*. Note that a unique process stage cannot be determined simply using instantaneous value of $\mu(.)$ because $\mu_Z(DORP_k)$ is associated to both stage 1 and 3. Here, a simple triangular function for $\mu_Z(DORP_k)$, $\mu_D(DORP_k)$, and $\mu_I(DORP_k)$ is adopted. These functions can be determined from the slopes of a typical process profile. The membership functions are shown in Figure 7.

## EXPERIMENTAL SET-UP

The schematic of the experimental set-up is shown in Figure 8. All the experimental runs were performed using synthetic wastewater containing metal ions of $Pb^{2+}$, $Cu^{2+}$, $Ni^{2+}$, $Zn^{2+}$, and $Cr^{6+}$. Reagent grade chemicals of sulphate salts for all cations (Cu, Ni, Zn, and Pb) except for $Cr^{6+}$, where $K_2Cr_2O_7$ was used, were diluted with distilled water in all test solutions.

The synthetic wastewater is rapidly stirred by a mechanical mixer in order to ensure a complete mixing of the wastewater and reducing agent. The ORP electrode transmits its analog signal through an analog-to-digital interface card to a personal computer for on-line measurement, data analysis and control purposes. The reducing agent, ferrous

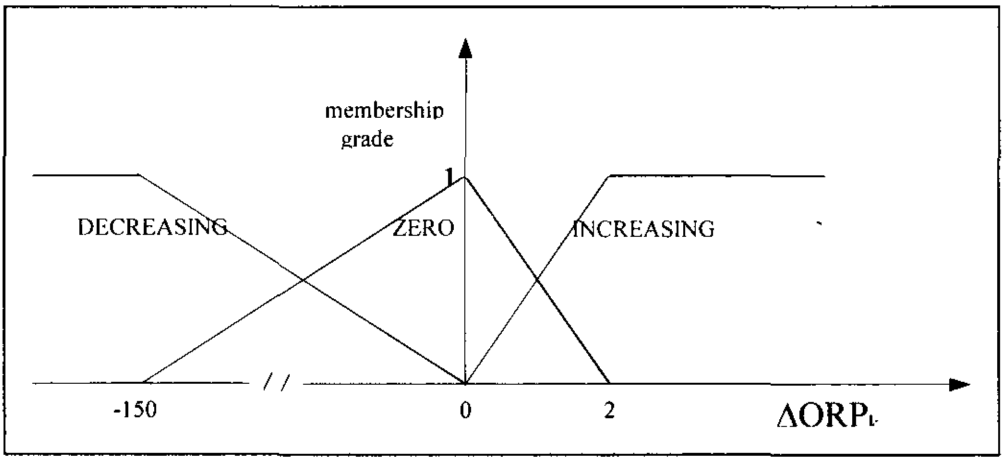


***Figure 7. Membership Functions***

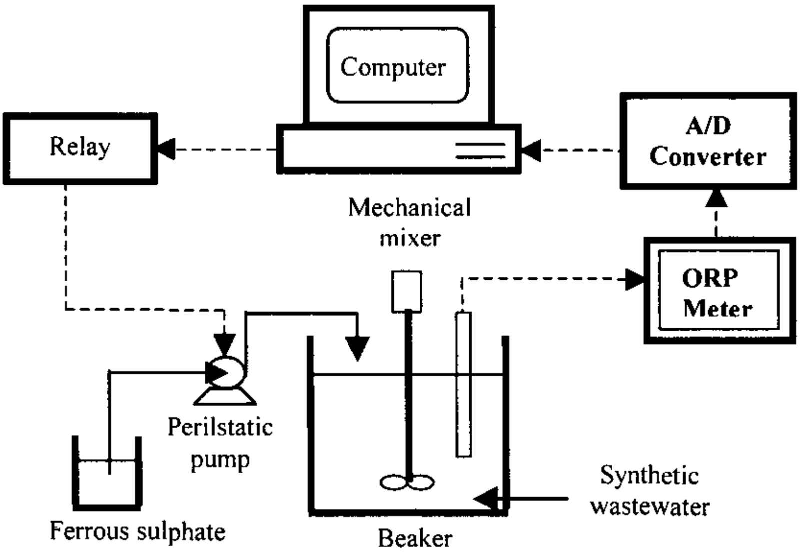


***Figure 8. Experimental Set-up for Chromium Reduction***

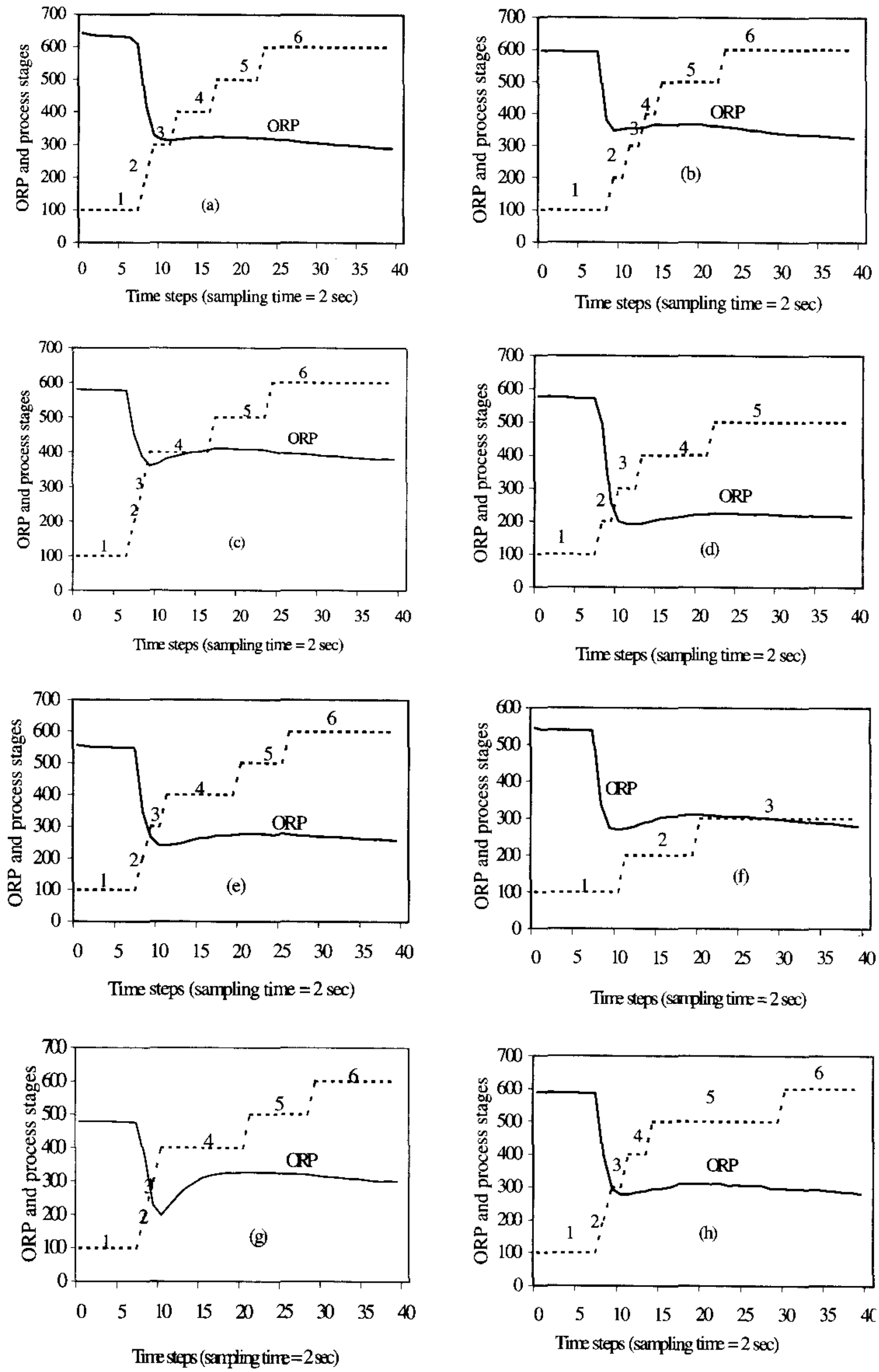


*Figure 9. Results for Various Runs*

sulphate is added at a fixed flow rate via a peristaltic pump that is controlled by a relay connected to the PC parallel port. The sampling time used is 2 seconds.

This simple on–off control is adopted due to robustness and low hardware cost. This approach is adopted here because this project is part of the research program to develop a low-cost treatment process to treat electroplating waste generated by many small companies.

## EXPERIMENTAL RESULTS

In this study, to enable the same conditions to be duplicated when testing different controller strategies, ORP readings were logged into the computer when ferrous sulphate was dosed at constant rate. These data were then used to investigate the effectiveness of various control methods. The experimental results presented here is based on the recursive combination and the devaluation factor $a$ is 0.4. The results obtained for ten different sets of run under various conditions are shown in Figure 9. All the runs except for runs (d),(f), and (i) show that the pump was switched off (stage 6) at the right time.

Run for set (f) shows that the algorithm was not working as it stuck at stage 3. It was found that the reason for this was that in certain stages such as stages 2 and 3, the duration the process was in these stages was very short to enable the appropriate belief levels to be accumulated and exceed the threshold level required to trigger transition of the finite state machine to another stage. To overcome this problem the devaluation factor $\alpha$ can be increased, but this will make the algorithm more sensitive to noise. Alternatively, it is proposed that the mass function for evidence for stage 2 is taken as the sum of the mass functions for stage 2 and stage 4. The mass functions for stage 2 and 3 cannot be combined (although this seems to be more appropriate) because the evidence for stage 3 (zero slope) is the same as the evidence for previous stage (stage 1). With the proposed change, the block in stage 2 of the algorithm flowchart in Figure 6 will be modified as follows:

<u>compute mass functions</u>

$m_K(S1) = m_Z(\Delta ORP_K)$

$m_k(S2) = m_D(\Delta ORP_k)$

$m_k(S4) = m_I(\Delta ORP_K)$

<u>aggregated beliefs</u>

$m_{0,k}(S1) = m_{0,k-1}(S1) \oplus (m^{\alpha}{}_K(S1) + m^{\alpha}{}_K(S4))$

$m_{0,k}(S2) = m_{0,k-1}(S2)\, '\oplus (m^{\alpha}{}_k(S2) + m^{\alpha}{}_k(S4)$

With this modification, the result obtained using the data for the previous run (f) is shown in Figure 10. With this modification it may occur as shown in Figure 10 that some identified stages

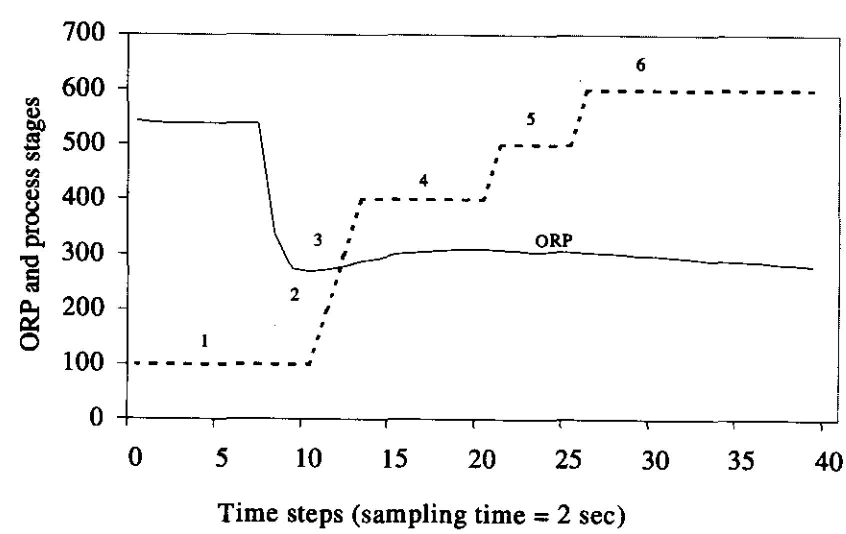


***Figure 10. Result for Set (f) Using the Modified Algorithm***

do not exactly coincide with the actual process, but what is really important is that the final stage is correct. Runs (d) and (i) show that the algorithm stuck at stage 5 since the negative slope at stage 6 was too small to be detected. In practice stopping the pump at stage 5 (when the ORP reached the peak value) is acceptable in most cases. However, as a safety factor it is desirable to be slightly overdosed, hence the pump will only be stopped when stage 6 is reached. To handle the situations such as depicted in runs (d) and (i) the algorithm can be automatically forced to switch to next stage 6 after it was detected that the state machine was in stage 5 for a certain preset duration.

## CONCLUSIONS

A new algorithm using DS's evidence theory has been presented to automate the process of removing toxic hexavalent chromium in wastewater, which, at present, no satisfactory control has been implemented.

A new method for combining sequences of evidences gathered over time is also proposed that can recognize the relative importance of evidences gathered at different time. The proposed algorithm has been successfully implemented in the laboratory scale model.

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