

on Figure 1 is the true process value. The "measurement" can be described as a second-order autoregressive integrated moving average (ARIMA) (MacGregor, 1988) with superimposed step and ramp changes.

The line labeled "filtered process variable" is the filtered value calculated by the self-tuning filter ( $M = 5$ ) with  $E_{pv} = 4$  units. At the bottom of the graph are curves that indicate the standard deviation of the process variable as calculated by (15) and the filter time constant as calculated by (18). Occasionally events cause  $\tau_f$  to be extremely large, so there is a ceiling on  $\tau_f$  of  $50T$  for visual graphical convenience. Note that the estimated  $\sigma_{pv}$  is close to either the true 8 units or 2 units in spite of the presence of autoregressive drift, ramp, and step changes. Note that the filter time constant changes only in response to process variance in spite of the other transient effects. (While the period from the 1st through the 300th sample was intended to have a standard deviation of 8 units, the confluence of random numbers at the 20th sample caused large measurement deviations that the self-tuning filter detected. It adjusted accordingly.)

Note that the "filtered process variable" curve lags behind the "actual" process variable. This is an expected effect of the first-order filter. Also note that where the process variance is high the lag is greater than when the process variance is low. This is the desired effect of the self-tuning filter. At low process variance, the filter time constant is low and the filtered value is responsive to process changes. At high process variance the filter time constant is high and uses more data to obtain the average. At all cases the 95% confidence interval,  $E_{pv}$ , was 4 units.

### Conclusion and Critique

A method for automatic adaptation of a time constant for a first-order filter has been developed by use of ele-

mentary statistical concepts. Toward developing an easy to implement and computationally inexpensive method, the author has incorporated simplifications grounded in this experience. The method has been demonstrated on a wide range of simulated conditions and has two advantages over standard practice. First, the user specifies the desired 95% confidence interval for the filtered value instead of a secondary parameter, the filter time constant. Second, the method automatically adjusts the filter time constant as the process variability changes to minimize filter lag while maintaining the desired accuracy.

The method assumes that the sampling period is small in comparison to real changes in either process level or variability and that the noise is a random Gaussian fluctuation with a mean of zero.

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## Effect of Turbulence Damping on the Steady-State Drop Size Distribution in Stirred Liquid-Liquid Dispersions

With the help of a recent model for the drop size distribution in stirred liquid-liquid dispersions, the effects of turbulence damping and coalescence, individually, on the characteristic drop sizes are investigated. The outcome of this work, which is based on an unstable dispersion where both coalescence and breakup occur simultaneously due to mixing, lead us to conclude that drop sizes in such systems are predominantly governed by turbulence damping, with coalescence playing an indirect role.

### Introduction

A simple model for predicting the steady-state drop sizes in stirred systems has been recently proposed (Cohen, 1990). The approach considers a large number of drops dispersed in a continuous fluid being stirred rapidly. Due to stirring, the drops continually coalesce and break up, and as a result, a steady-state drop size distribution is observed after a period of time.

Everyone of these drops is assumed to be composed of a certain number of primary droplets, each having a diameter,  $d_{\min}$ , where the subscript min refers to "minimum". Thus, the primary droplets are the smallest units that exist in the dispersion. In relation to the theory proposed by Hinze (1955), it is important to note that  $d_{\min}$  is the most stable droplet size determined by the Weber number,  $We$ , and the dispersed-phase volume fraction or holdup,  $\phi$  (Godfrey et al., 1989 and references within). We may consequently assume that for a given  $We$  and  $\phi$ , any droplet larger than  $d_{\min}$  could break down to form smaller droplets, while the minimum droplet size in the dispersion

remains fixed at  $d_{\min}$ . Very briefly, therefore, the model is based on the assumption that (1) drops larger than  $d_{\min}$  result from the coalescence of smaller droplets, or the breakup of larger drops, and (2) while the primary droplets of size  $d_{\min}$  can coalesce to form larger drops, they cannot break down to form smaller droplets.

Avoiding the details of the derivation, the Sauter mean diameter,  $d_{32}$ , of the drops in the suspension is shown to be given by (Cohen, 1990)

$$d_{32}/d_{\min} \approx Z^{1/3} \quad (1)$$

where

$$Z \equiv \ln N_0 - \ln(\ln N_0 - \ln \ln N_0) \quad (2)$$

and

$$N_0 = \frac{\phi V}{\pi d_{\min}^3 / 6} \quad (3)$$

Note that  $N_0$  is simply the total number of the primary droplets in the suspension having volume  $V$ , should the