Automating the Dow Theory with the Fractal Wave Algorithm

by E. W. Dreiss

E. W. (Bill) Dreiss graduated from the Massachusetts Institute of Technology in 1964 with a BS in electrical engineering. In 1966 he received an MBA from Harvard Business School. In 1973, after several years of experience in mathematical and financial modeling, he took a position with E.F. Hutton & Co. in San Francisco as a commodity broker. In 1975 he left to become a principal and chief trader with Commodity Consultants, Inc., one of the first firms to manage large amounts of risk capital using mechanical trading methods. In 1976 he established San Miguel Associates, which was an active and successful Commodity Trading Advisor until February of 1984. Mr. Dreiss then turned his attention to computer consulting and software development, while continuing to trade commodities for his own account.

Mr. Dreiss is responsible for a number of technological innovations related to trading managed commodity accounts. He was the first CTA to balance diversified portfolios on the basis of expected risk per trade, and originated the concept of trading a short term system only in the direction of the longer term trend. He has continued his research into innovative approaches to commodity trading, developing trading methods based on recent breakthroughs in chaos theory, fractal geometry and artificial intelligence.

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Approaches to the technical analysis of markets can be divided into two general categories, numerical and pattern-recognition. An example of a numerical method is the moving average, while trendlines would be a simple example of a pattern-recognition technique. While some trading systems employ a mixture of the two types of analysis, most rely primarily on either one or the other. Prior to the widespread use of computers, technical analysis was virtually synonymous with pattern-recognition. This was largely due to the difficulty of testing and updating any but the simplest numerical methods by hand. It was much easier and more intuitive to use charts for identifying patterns and trends. A drawback to chart reading was that it was more art than science and it was difficult to prevent bias and emotion from clouding the chart interpretations.

Computers turned the tables by providing the calculating power necessary to develop mechanical trading systems based on sophisticated numerical methods, which could be traded objectively and rigorously tested. This has resulted in a major shift of focus in the last 20 years towards moving averages, oscillators, stochastics, momentum, etc. While it is easy to program a computer for a wide variety of numerical calculations, programming a computer for pattern recognition is far more difficult. Therefore, the usefulness of the standard methods of pattern recognition (Dow Theory, Elliott Wave Theory, chart pattern analysis, etc.) continues to depend upon the individual skills of the practitioner.

The Fractal Wave Algorithm (FWA) developed by Art von Waldburg is a powerful new tool which provides a basis for objective chart analysis. *(Editors Note: see TTB May 1990 for interview with von Waldburg.)* Although the FWA was originally programmed to assist in counting Elliott Waves, it soon became clear that it had a more general application. The logic used in defining turning points proved identical to that used by the Dow Theory to identify trend reversals. In the process of automating Dow Theory reversals, the FWA also generalizes Dow's model by incorporating a fractal structure similar to that found in the Elliott Wave Principle.

The FWA is fractal in that it marks waves containing waves, containing waves, etc., starting at the lowest level of price activity available to the program. The number of price activity available to the program. The number of nestings or "levels" are limited only by the amount of data provided, whereas the Dow Theory deals only with three levels of trend: primary, secondary and minor. Since the Dow Theory trends are identified by guidelines pertaining to

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duration and not by a set of specific rules, labeling the trends remains a matter of individual interpretation. The FWA, however, is mechanically constructed by applying the Dow criteria to a simple price pattern in a recursive manner to construct progressively higher level waves. Once these objectively determined points are marked, they can be used as the basis for developing mechanical systems applying classical methods of chart analysis.

The simplest example of using the FWA to model classical chart analysis is its application to identifying Dow trends. If we define an "up" day as a day which closes higher than the previous day and a "down" day as a day which closes lower than the previous day, the lowest level (LO) turning point can be marked on any day where a down day follows an up day or an up day follows a down day. The next level (L1) turning point is marked when the most recent LO high or low is penetrated after a mark in the opposite direction; this results in alternating highs and lows. The next level (L2) is marked on penetrations of the most recent L1 highs and lows, and so on. When this algorithm is applied to stock and commodity price charts, the L1 marks identify Dow minor trends, the L2 marks identify secondary trends and the L3 marks identify primary trends.

The FWA can be set to operate in two different modes, "weak" and "strong". The weak version is as described above and marks a turn on any penetration of the high/low for the next lower level. This allows a trend turn to be marked on a Dow "nonfailure swing". A Dow "failure swing" requires that the penetration of a lower level low be accompanied by a prior lower level high that is lower than the previous lower level high in order to mark a top (and vice versa for a bottom). This is required for the FWA operating in the strong mode. Notice that the strong mode requires alternating "zigzag" price patterns at a particular level. This gives the marked chart more of a fractal look than with the weak FWA, although the logic is fractal in both cases. It is also possible to combine the weak and strong turns into a "hybrid" algorithm that allows for a weak mark following a strong mark, but requires a strong mark after a weak one. This algorithm has a sensitivity intermediate between weak and strong, but closer to weak due to the prevalence of the strong pattern in market data.

Six years (1984-89) of continuous data for 14 different commodities were marked using the weak, hybrid and strong algorithms and the number of turns for Levels 1 through 3 were tabulated for each combination. These turn counts were then used to compute the average duration from low to low for each of the 4 levels. The aggregate results are presented in Table 1. The average durations given above roughly correspond to the approximate trend lengths used by Dow to identify the minor (L1), secondary (L2) and primary (L3) trends (see Technical Analysis of Futures Markets, by John J. Murphy for a discussion of Dow Theory trends and reversals).

Table 1. Average Duration from Low to Low for FWA Levels 1-3 (weeks)

Algorithm	L1	L2	L3
Weak	3.2	12	42 (10 months)
Hybrid	3.5	14	54 (1 Year)
Strong	5.4	30	181 (3.5 Years)

FRACTAL TRADING SYSTEMS

The minor, secondary and primary trends can be used to construct short, intermediate or long term systems, or can be combined to trade shorter term moves in the direction of a longer term trend. A simple example would be to trade Level 1 moves in the direction of the Level 2 trend. Another possibility would be to combine weak and strong turns; for instance, entry might be on a strong L2 turn with exit on a weak L2 turn.

The results of two such systems tested on 6 years of commodity data are shown in Tables 2 and 3. These systems incorporate the following rules to make them realistically tradable. First, even though wave turns are marked using closing prices only, entries and exits are intraday penetrations of the intraday highs or lows corresponding to the marked turns. This means that sometimes turns are "anticipated" by the system that are not confirmed by the close. At other times, turns may be marked without entries or exits being triggered. Second, a $3,000 per trade equity stop is used as the initial stop

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loss for those cases where the calculated stop loss is inordinately far away. (The $3000 equity stop is appropriate to an account capitalized with $100,000 and would be scaled proportionately for other account sizes.) In addition, $100 is deducted per trade for commission and slippage.

The results of these systems compare favorably with those of other mechanical back-tested systems (for example, those listed in The Dow Jones-Irwin Guide to Trading Systems, by Bruce Babcock, Jr.). The advantage of these fractal systems is that they are simple (a low number of degrees of freedom) and virtually parameter free, a feature which distinguishes them from numerical systems. While these systems have not been tested extensively in real time, one would expect the future performance to be more consistent with the past than for systems which are more complex and/or highly optimized.

Fractal systems can also be used to confirm the performance of non-fractal systems. The FWA can be used as a universal system template, and many mechanical systems can be matched to corresponding fractal systems which produce similar results as to trading frequency and duration. Results for such a system are presented in Table 4. If the fractal system produces trades in roughly the same places as the non-fractal system produces significantly greater profits than its fractal equivalent, one might suspect that the non-fractal system has been data-fitted by excessive optimization.

All commodity traders have experienced markets in which it would have been virtually impossible to make money, except by pure luck. Other markets would result in profits for almost any trend-following system. System performance for a particular commodity is generally compared to that achievable with other commodities or alternative

Table 2. Trade L1 Trend in the Direction of the L2 Trend with $3000 Stop

	Closed Trades	Profitable Trades	Percent Profitable	Total Profit or Loss	Average Profitable Trade	Average Losing Trade	Maximum Drawdown	Average Profit per Trade
Coffee	69	22	32%	55349	5202	-1257	-15294	802
Sugar	83	26	31%	694	956	-424	-6366	8
Crude Oil	70	30	43%	48370	1382	-577	-3250	262
Copper	85	24	28%	15278	1761	-442	-10312	180
Cotton	70	22	31%	2130	1648	-711	-8795	30
Corn	71	21	30%	-2044	524	-261	-3394	-29
Soybean Meal	68	32	47%	20540	1081	-390	-2780	302
Soybean Oil	82	30	37%	4122	825	-397	-3396	50
Gold	93	26	28%	-1560	1364	-553	-13930	-17
Platinum	81	23	28%	-3400	1420	-622	-11600	-42
Yen	63	21	33%	39800	3458	-781	-9425	632
Swiss Franc	61	30	49%	48613	2605	-952	-7037	797
T-Bills	59	18	31%	-4700	1222	-651	-14200	-80
T-Bonds	71	27	38%	37873	2897	-917	-10594	533
Average	**73**	**25**	**35%**	**16505**	**1882**	**-638**	**-8598**	**245**

Table 3. Enter on Strong L1 Penetration, Exit on Weak L1 Penetration with $3000 Stop								
	Closed Trades	Profitable Trades	Percent Profitable	Total Profit or Loss	Average Profitable Trade	Average Losing Trade	Maximum Drawdown	Average Profit per Trade
Coffee	26	10	38%	58591	9362	-2189	-10521	2254
Sugar	27	7	26%	-2565	2126	-872	-11324	-95
Crude Oil	22	8	36%	13300	3579	-1095	-5350	605
Copper	29	10	34%	15023	2629	-593	-6470	518
Cotton	26	9	35%	17340	3915	-1053	-7990	667
Corn	27	10	37%	494	630	-342	-1913	18
Soybean Meal	23	7	30%	10650	3176	-724	-5150	463
Soybean Oil	26	11	42%	2004	1180	-732	-3742	77
Gold	34	10	29%	1320	2793	-1109	-11320	39
Platinum	34	12	35%	-620	1709	-960	-9715	-18
Yen	16	11	69%	52962	5562	-1645	-4937	3310
Swiss Franc	22	12	55%	30738	3932	-1645	-3850	1397
T-Bills	17	10	59%	6075	1490	-1261	-4500	357
T-Bonds	21	7	33%	30494	7815	-1730	-13239	1452
Average	**25**	**10**	**40%**	**16843**	**3564**	**-1139**	**-7144**	**789**

investments. The FWA can be used to determine a measure of maximum performance for a particular market, by calculating the cumulative absolute price differences between turning points of a given level. Actual or simulated performance for systems trading with similar trade frequency and duration can then be compared to this upper bound of performance. If the FWA performance maximum is small or negative, it would be unrealistic to expect any system to do well. In fact, if one did perform better, data-fitting would be strongly suspect.

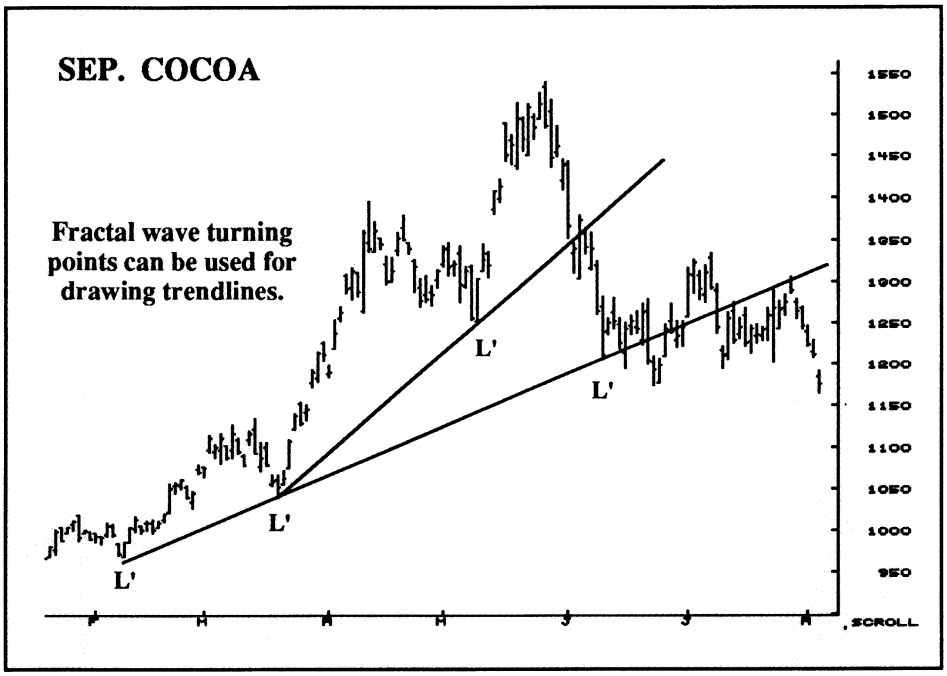

Table 4. Fractal Simulation of a Non-Fractal Trendline System with $3000 Stop								
	Closed Trades	Profitable Trades	Percent Profitable	Total Profit or Loss	Average Profitable Trade	Average Losing Trade	Maximum Drawdown	Average Profit per Trade
Coffee	18	7	39%	42870	9266	-2000	-10124	2382
Sugar	18	5	28%	8046	3211	-616	-3675	447
Crude Oil	19	7	37%	7990	2779	-955	-4220	421
Copper	21	6	29%	17463	4365	-582	-4100	832
Cotton	22	8	36%	12145	3710	-1252	-8520	552
Corn	18	7	39%	1719	884	-406	-2631	95
Soybean Meal	18	4	22%	7650	4285	-678	-5550	425
Soybean Oil	18	9	50%	4226	1175	-706	-1552	235
Gold	22	7	32%	7040	3309	-1075	-7790	320
Platinum	24	7	29%	-190	2372	-988	-11240	-8
Yen	12	7	58%	39300	6666	-1472	-3237	3275
Swiss Franc	16	9	56%	30950	4608	-1504	-6037	1934
T-Bills	14	7	50%	10825	2486	-939	-4775	773
T-Bonds	14	7	50%	31381	6356	-1873	-9564	2241
Average	**18**	**7**	**40%**	**15815**	**3962**	**-1075**	**-5930**	**995**

The FWA can also be used to identify more complex chart patterns than Dow trends. Turning points for a particular level could be used for drawing trendlines (see cocoa chart on page 11), triangles or pennants and identifying patterns such as head-and-shoulders. The FWA can assist in labeling Elliott Wave counts, although the number of lower level waves contained in the next higher level wave will not always be 3 or 5.

The Dow Theory is the grandfather of technical analysis methods and is still widely respected. Most subsequent chart analysts have used Dow's work as a starting point, including R.N. Elliott and Henry Wheeler Chase. The FWA provides the means to carry on this work with greater precision and opens the way to mechanical pattern-recognition systems as rich and diverse as those using numerical methods.

Editors note: We wish to than Bill for his excellent article and for sharing the results of his research with us. We look forward to publishing more of his work in future issues.