Dejonckheere, J., Disney, S.M., Lambrecht, M.R. and Towill, D.R., (2003), "Dynamics of aggregate planning", Production Planning and Control, Vol. 14, No. 6, pp497–516. DOI: 10.1080/09537280310001621967.

THE DYNAMICS OF AGGREGATE PLANNING

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Abstract

Recent software developments in system modelling via transfer function analysis now enables a much broader understanding of the dynamics of aggregate planning to be gained. In particular it opens up the possibility of exploiting filter theory as a focal point during algorithm design. This is particularly attractive in view of the fact that we have established, via transfer function models, that there is commonality between HMMS and the order-up-to replenishment rules used extensively within both local and global supply chains. Filter theory allows us to relate these dynamics directly to present day production planning strategy as observed in much industrial practice. It covers the spectrum of production strategies recently identified as preferred industrial practice. These strategies range from "level scheduling" (i.e. lean production) right through to "pure chase" (i.e. agile manufacture) with appropriate simple algorithmic control support via APIOBPCS software.

Key Words:

Aggregate Planning: Holt, Modigliani, Muth and Simon (HMMS) algorithm: Transfer Functions: System Dynamics: Filter Theory:

1. Introduction

This paper is concerned with the relationship and analogues between the dynamic responses of factory aggregate planning systems and those of production ordering systems used at the individual SKU level. As a benchmark for the dynamics of aggregate planning we study the responses obtained for paint factory control as evaluated from the HMMS algorithm (Holt, Modigliani and Simon (1955), Holt, Modigliani, Muth, and Simon (1960)) for both "perfect" operating conditions and with realistic forecast errors and product delays. Because of the established use by industry of simple planning decisions such as the "Level Scheduling" and "Chase" rules (Silver, 1974) (also known as "Lean" and "Agile" production, Towill and Christopher, 2001), we also compare their dynamic responses to the HMMS performance. The trade-off in inventory/capacity/workforce swings is then evaluated via simulation. Our conclusion is that if industry needs simple robust decision rules for this purpose, (Monniot, Rhodes, Towill, Waterlow, 1987), then those based on the APIOBPCS algorithm (John, Naim and Towill, 1994) are strong contenders. This is readily shown by developing "ad hoc" APIOBPCS models capable of matching HMMS dynamic performance.

Recent seminal industrial survey based research by Buxey (1995) supports the case for using simple decision rules. In such a situation the "filter" concept has many practical advantages in assessing and predicting dynamic response. This is especially so when seeking improved compromise designs which seek to redress the balance between the extremes of "Level Scheduling" and "Chase" scenarios. Yet inspection of the HMMS outputs for typical inputs shows that good filtering of volatile demands has actually been achieved. So if we select an APIOBPCS design which had broadly equivalent dynamic performance then we can enable similar damping of demand via a much simpler algorithm. Furthermore this mimics the type of decision-making undertaken by human production schedulers. "Fine tuning" of the parameters is then best done by management debating and then choosing the demand frequency range to be removed by the algorithm. This can be set on an intuitive basis, preferably cross-checked by simulating the algorithmic response to historical data. It is thus the production manager who interactively decides how near to "level scheduling" or how near to "chase" mode he wishes his operations to be. This harks back to the "cut and try" philosophy ably demonstrated by Buffa (1969).

Aggregate planning algorithms are remarkably similar to supply chains in their dynamic behaviour. This is hardly surprising, since the basic equations used therein can be described as making decisions based on current states such as workforce, capacity, inventory, orders in pipeline, and some forecast of future demand. In this respect it is similar to supply chain decision-making algorithms. But whereas the consequential supply chain problems such as bullwhip are well documented (Lee, Padmanabhan and Whang 1997, Towill and McCullen, 1999), it is less well known that algorithms such as HMMS (Holt, Modigliani, Muth, and Simon, 1960) suffer from the same phenomena. Thus the possibility of bullwhip is a further trap for the unwary, to which may be added those difficulties encountered when establishing suitable cost models prior to optimisation.

Our viewpoint of how the dynamics of aggregate planning and ordering systems relates to production strategy is summarised in Fig. 1. Note that we are concerned only with the **P**roduct **D**elivery **P**rocess (PDP). In tailoring available mechanisms to ***our*** company we need to know what is our business; what resources are needed and when; how many of which Stock Keeping Units (SKU’s) do we make today; and how do we deliver these orders. This paper specifically considers the dynamics at level two and level three (aggregate planning and ordering systems) and exploits their similarity. It shows how an understanding of one approach transfers insight to the other. Finally, we relate our theoretical concepts to the industrial practices identified by Buxey (2001). We share his conclusion that it is production strategy, which determines the algorithms to be implemented in the real world, and not the other way around. Furthermore we demonstrate that simple tuneable filters such as the APIOBPCS algorithm (John, Naim and Towill, 1994) will do the job. To do this requires us to experimentally determine broadly equivalent ***z*** transfer functions between HMMS and APIOBPCS.

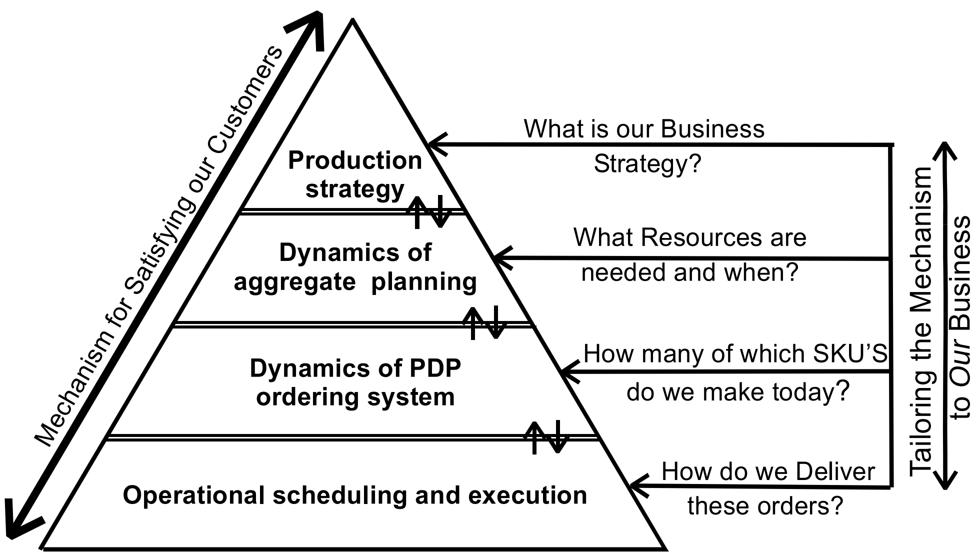


Figure. 1. Integration of Aggregate Planning and the Product Delivery Process (PDP) within the Mechanism for Satisfying our Customer.
(Source: Authors, adapted from Listl and Notzon, 2000)

2. Characteristics of the Operations Research and Filter Theory Approaches

The study of DSS has a long and distinguished history particularly amongst the Operational Research (OR) community. This dates back to the classic HMMS algorithm (Holt, Modigliani, Muth and Simon, 1960) and its many variants and updates typified by Jones (1967), Bertrand (1986) and Lambrecht, Luyten and Eecken (1982). Corresponding mathematical analysis of production systems based on what has become known as the servomechanism approach started with Tustin (1952). The next group of researchers concentrated on controlling the dynamic response via placement of the system poles (i.e. roots of the characteristic equation) using Laplace Transforms (Simon, 1952) and a short while later via **z** Transforms (Vassian, 1955). We must add a note of caution here. There is much more to shaping dynamic response than pole placement, since it is the system zeros inherently due to the forecasting channel that frequently induces bullwhip (Dejonckheere et al, 2002b).

The system optimisation problem was subsequently re-cast in the form of minimising a cost function composed of storage and production adaptation costs (Adelson, 1966 and Deziel & Eilon, 1967). Both of these papers made significant contributions to our understanding of aggregate planning. But despite the considerable difficulty in establishing a realistic cost model this HMMS style approach became extremely popular amongst OR researchers. We term this ideology the implicit filter design method because it concentrates on minimising the cost function and then hoping that the consequential filter performance is acceptable. The latter property is far from guaranteed by this approach. Table 1 compares the salient features of the OR and Filter approaches (Towill et al, 2001). Manifestly both techniques could result in similar optimal designs for a manufacturing system or indeed for a supply chain, but the routes to their solution are very different.

Our filter theory methodology herein is based on the same mathematical principles as the OR approach as defined by Table 1. However we reverse the procedure since we are concerned upfront with explicit filter design in which good dynamic performance is a prerequisite. The argument is that cost control follows from good dynamic design, and we especially need to ensure high customer service level concurrently with small swings in capacity requirements. At the heart of the explicit filter design approach is the complete understanding of how the system transfer function governs dynamic response. For example, the dominant roots of the characteristic equation are important factors in determining system bullwhip, but it is only one factor. Thus a conservative placement of the dominant poles of the feedback loop can fail to adequately dampen the bullwhip system in the presence of exponential smoothing of feed-forward demand of orders received by the factory (Towill, 1982). In system engineering terms, pole-placement as a controller of dynamic response has broken down because of the presence of predictive elements within the system. In contrast, for linear operation, transfer function techniques are all embracing. Hence given the transfer function of a manufacturing system the filter characteristics are uniquely defined for all inputs. So the design problem becomes "given the expected inputs and desired outputs, what transfer function will deliver the necessary performance?"

CHARACTERISTICS	OR APPROACH	FILTER APPROACH
System Model	Integral/difference equations	Transfer functions
Typical Assumed Stimuli	Random excitation	Sinusoidal excitation
Methods of Analysis	s/ **z** transforms Probability theory	s/ **z** transforms Fourier transforms
Performance Criteria	Production/inventory variances	Production/inventory power spectra
Optimisation Procedure	Minimise quadratic cost function	Minimise deviation from "ideal" filter
Design Emphasis	Implicitly smooth production/inventory swings	Explicitly smooth production/inventory swings
Bullwhip Consequences	Somewhat arbitrary	Reduce by design
Financial Implications	Precise according to cost function	Somewhat arbitrary

Table 1. Comparison of the Operational Research and Filter Approaches to DSS Selection in Supply Chain Design (Source: Towill et al, 2001)

3. Reasons for Using Transfer Function Techniques

Transfer function techniques are used extensively in the analysis and design of hardware feedback control systems (Towill, 1970). A transfer function is a specialist mathematical model used to describe a particular system, and may be determined from differential/difference equations and/or experimental results obtained from tests on a physical artefact. For a linear system the transfer function enables the response to any stimulus to be predicted with confidence. Via small perturbation theory, certain classes of non-linear systems may also be designed via transfer function techniques. Furthermore "linear" theory permits the selection of the "best" controller in some practical scenarios even where there are capacity constraints within the system (Towill, 1969). The practical implication of this result is to choose the controller that limits the likelihood of the system operating in the capacity limited mode.

Although Axsäter (1985) suggested that such transfer function techniques were best suited to the aggregate planning level of Fig. 1, it has been shown that they have a significant part to play in the design of ordering algorithms. As an example, Towill (1982) successfully applied the transfer function concept to a generic manufacturing system. So although the existence of bullwhip for this same system had been previously demonstrated via simulation (Coyle 1977) the new mathematical analysis proved this fact analytically and furthermore directly pinpointed the cause. This eliminated the need for trial and error investigation and subsequently provided a general guideline for systems design. This is an extremely important aspect in a design procedure that explicitly seeks to eliminate as many aspects of supply chain uncertainty as possible. Additionally the generic transfer function was mapped into a standard coefficient plane format, thereby enabling 'best practise' parameter settings to be readily transferred in from previously published results for hard systems artefacts (Towill, 1982). In other words the transfer function is a mechanism for predicting the dynamic performance of a new system from an understanding of "similar" existing systems whose physical characteristics may vary widely.

One consequence of the properties of this "design by analogy" approach is that we have confidence not only in the quality of our system, but a full understanding of why it is so successful. This is typified and exploited via recent bullwhip reduction techniques (Dejonckheere et al, 2000 and 2002b). An important adjunct of transfer function techniques is the ability to guarantee a stable design and then mould the system response according to specification. Careful shaping of feedforward and feedback paths is required (Horowitz, 1963), which is readily done in the frequency domain. Hence the particular relevance of filter theory to supply chain design. For example, the "idealised" system with "perfect" forward path forecasting soon breaks down under "real world" conditions. This is readily predicted from filter theory.

4. The Concept of the 'Ideal' Filter

Dynamic systems must be designed to follow command signals (the 'signal'), and yet at the same time reject the unwanted disturbances (the 'noise'). To achieve this objective, systems may be synthesised using time domain concepts, or via frequency domain concepts whichever is most convenient. In either case, the required performance data can be obtained via mathematical analysis (at least in theory), or by simulation. An advantage of the filter concept is that it forces the "client" and the system designer to discuss and think carefully about their definitions of "command" and "noise" signals as appropriate to this specific application. For example, do we or do we not consciously change workforce levels for weekly changes in demand? Should the answer be "no" then the designer needs to ensure that weekly variations are adequately filtered out by the DSS ordering algorithms. If the answer is "yes" then some consequential volatility in workforce requirements must be anticipated.

If the mathematical analysis route to system design is followed, then as complexity increases the time domain route rapidly becomes unattractive. Fortunately this is not the case in the frequency domain, at least for understanding linear systems, where each additional sub-system simply generates a further change in amplitude ratio and phase of the 'steady-state' frequency response. Specifically, the need for the complicated process of convolution in the time domain is replaced by straightforward vector multiplication in the frequency domain. Consequently a large body of knowledge has been built up over many years relating real-world 'mission performance' to the idealised frequency response (Towill, 1975).

What is actually implied by the method is the assumption that both the 'signal' and the 'noise' can be understood and represented by a limited number of sine waves. These can be obtained from actual operating data via Fourier analysis (or more likely, by 'informed' judgement). The regions corresponding to 'signal' and 'noise' components are then sketched as a function of frequency. Usually there will be some separation between these two regions. Sales and Production Departments may well have differing views as to where this should be.

Since we would like the signal to be perfectly transmitted, the 'perfect' filter, would have an amplitude ratio (or gain) of unity at the signal frequencies. In contrast, we wish to reject the noise, so at these frequencies we wish to see an amplitude ratio (or gain) of zero, (Towill and Del Vecchio, 1994). Thus the concept of the ideal filter may be represented as an envelope of amplitude ratios which take the value of either one or zero. This is depicted in Fig. 2 which represents the particular case of the Low Pass Filter. For instance in supply chains this might correspond to the desired relationship between marketplace consumption and consequential orders placed on the factory. So slow and hence genuine changes in demand pattern would be considered important, and hence tracked by the system. In contrast rapid daily fluctuations would be seen as random "noise" and be filtered out.

If this idealised state of affairs is actually achieved, then the filter output will be identically equal to the uncontaminated input signal under all conditions. In practice, such perfection is difficult to achieve. Hence frequency response of an acceptable sub-optimal filter (i.e. one that is good enough for the specific purpose) is substituted. Such a filter does not have a transmission that instantly switches from one to zero at the cut-off frequency. Some rounding of the corners is inevitable and if as a consequence the amplitude ratio exceeds unity, then some "bullwhip" will result. It is part of the art (indeed, folklore) of filter design to choose a solution which gets rid of most of the "noise" but which at the same time loses very little of the "signal". Particularly at the ordering level shown in Fig. 1, there have recently been significant advances in enabling good trade-offs to be achieved (Dejonckheere et al, 2002b).

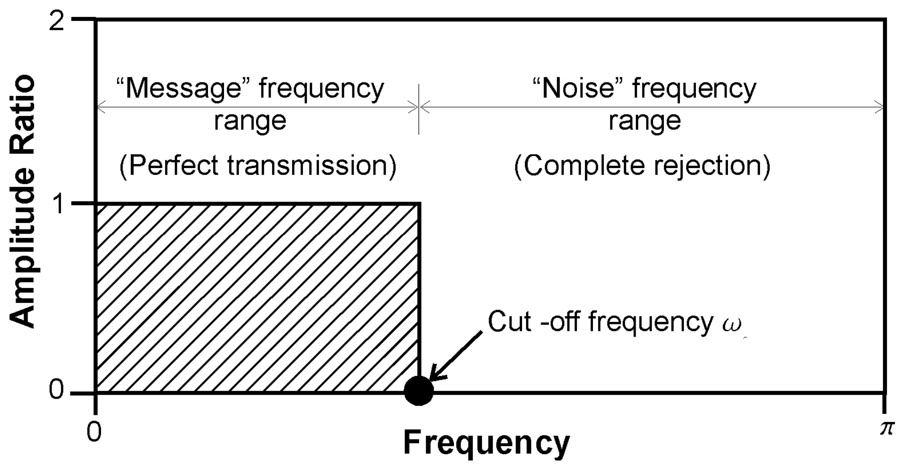


Figure 2. The "Ideal" Low Pass Filter Which Separates the "Message" from the "Noise" (Source: Towill et al, 2001)

5. Aggregate Planning as a Dynamic System: The Work of Ed Buffa

Aggregate planning increases the range of alternatives for capacity usage that must be formally considered by management. Our review in this section of the paper largely follows the seminal description of the aggregate planning problem by Buffa (1969). Despite the passage of time, his statement of the problems faced in operations management remains largely unchanged. Furthermore there is much in common with the approach of Buxey (2001), is an important reference in this paper and which surveys current industrial practice. The term "aggregate planning" usually includes scheduling in the sense of a programme; the terms "aggregate planning" and "aggregate planning and scheduling" are used almost interchangeably. The economic significance of Buffa's ideas is by no means minor. The concepts raise such broad basic questions (which are equally valid today) as: To what extent should inventory be used to absorb the fluctuation in demand? Why not absorb all these fluctuations by simply varying the size of the work force? Why not maintain a fairly stable work force size and absorb fluctuations by changing production rates through varying work hours? Why not maintain a fairly stable work force and production rate and let subcontractors wrestle with the problem of fluctuating order rates? Should the business purposely not meet all demands or pro-actively seek to smooth them via price changes (Hay, 1970).

In most instances it is probably true that any one of these extreme strategies would not be as effective as a balance among them. Each strategy has associated costs and, therefore, we seek an astute combination of the alternatives. We observe that if fluctuations are absorbed through changes in the production rate, overtime premium costs for increased workloads and probably idle labour costs (higher average labour cost per unit) for decreased workloads will also be absorbed. Usually, however, managers try to maintain the same average labour costs by reducing hours worked to somewhat below normal levels. When undertime schedules persist, labour turnover and the attendant costs are likely to increase. Unfortunately many costs affected by aggregate planning and scheduling decisions are difficult to measure and are not segregated in accounting records. Some, such as interest costs on inventory investment, are alternative opportunity costs. Other costs such as those associated with public relations and public image (the role of the good employer) are now measurable directly. However, all of the costs are real and bear on aggregate planning decisions.

An early example of OR optimisation in such a situation is shown in Table 2, which is adapted from Buffa (1969). We include it because of particular interest is the breakdown of the incremental costs incurred by adopting these three strategies. There are two extreme strategies that we have annotated in line with Silver et al (1998) terminology and which also tie-in with the "Lean" and "Agile" conundrum described by Towill and Christopher (2001). These are Level Scheduling (where inventory is used to buffer production from all fluctuations in sales) and "Chase" (where the production plan follows the sales variation directly and stock holding is minimised). A third pragmatic compromise strategy restricts capacity below that required by the Chase philosophy. In particular it results in control over production since no sub-contracting is required. However all three strategies require "a priori" judgements to be made by management. Typical are "what level?", "what capacity?" and "when to ramp up/ramp down?"

It is the pragmatic compromise solution that is "optimum" according to this particular set of circumstances with a projected annual saving of about 14%. Note that such compromises are frequently the "best" strategy at the ordering level of Fig. 1 (Dejonckheere et al, 2000). However, at the aggregate planning level, the cost model on which the optimisation is based is actually very difficult to establish under "real world" circumstances. Further cost modelling objections have been raised by Ackoff and Gharajadaghi (1996). Both references draw attention to the volatile and often fast-changing scenarios against which management decisions have to be made. Ackoff (1999) additionally questions whether managers can confidently use the output of modelling techniques they do not own.

MODEL PERFORMANCE CHARACTERISTICS \ PRODUCTION STRATEGY		"LEVEL SCHEDULING"	"PURE CHASE"	"PRAGMATIC SOLUTION"
Estimated Operational Requirements	Average seasonal inventory	9,800	1,150	2,275
	Average safety stock	3,400	3,400	3,400
	Average total inventory	13,300	4,550	5,675
	Relative Peak capacity required	100	181	133
Estimated Incremental Costs	Seasonal inventory cost	$M34.800	$M4.600	$M.9.100
	Labour turnover costs	0	$M16.430	$M16.430
	Overtime premium	0	$M6.000	$M52.800
	Extra subcontracting	0	$M6.000	0
	Total	$M34.800	$M33.030	$M30.810

Table 2. Cost Comparison of Three Alternative Production Strategies When Responding to a Specific Operating Scenario
(Source: Authors based on Buffa (1969))

6. Holt, Modigliani, Muth and Simon (HMMS Algorithm) Re-Visited

In order to achieve a good balance between the conflicting demands of production and inventory, the OR community have developed a veritable raft of solutions some more practically orientated than others. Algorithms include those by Holt et al (1960) subsequently known as the HMMS algorithm, Jones (1967), Orr (1962), Elmaleh and Eilon (1974), Silver (1974) and Lambrecht et al (1982). Whilst all of these propositions undoubtedly helped to smooth production (sometimes under very restricted conditions of demand volatility), it was in all cases achieved indirectly. That is, a cost function of sometimes dubious validity was first optimised and secondarily co-incidentally found that some smoothing actually resulted from using the resulting recommended algorithm.

The Linear Decision Rule of Holt, Modigliani, Muth, and Simon (1960) was developed in a quadratic programming approach to making aggregate employment and production rate decisions. HMMS is based on the development of a quadratic cost function specific to a particular company in question. Cost Components included regular payroll, hiring and firing of staff, overtime, inventory holding, back-ordering, and machine set-up charges. The quadratic cost function is then used to derive linear decision rules for computing work force levels and production rate for the upcoming period. It is based on forecasts of aggregate sales for a pre-set planning horizon. The two linear decision rules are optimum for the given model. HMMS sparked off an intense period of intellectual research trying to better the algorithm. Consequently HMMS has long been seen as a benchmark for the OR approach to aggregate planning. Furthermore the paint factory data used in their example has become a test bed on which various ideas have been evaluated.

In Fig. 3 we have reconstructed the well-known HMMS exploitation of their Paint Factory Data. These results will subsequently be used in Table 5 to benchmark a range of production strategies. Time Series representing the consumption order rate inventory level and workforce level are also shown. Yet Holt, Modigliani and Simon (1955, pp21) content themselves with statements as "With a perfect forecast the decision rule avoids, almost completely, sharp month-to-month variations in productions, but responds to fluctuations in orders that have a duration of several months". Their statement implies that there is a break point frequency corresponding to a period of around (say) 2 months. As we shall see later obtaining the complete frequency response characteristics is much more insightful to the operations manager. It enables us to make more detailed and meaningful comments on system performance. This is especially so (as we shall see later for the HMMS algorithm) when the response deteriorates under adverse conditions.

7. HMMS response Under Non-Ideal Conditions

Unlike most research into supply chain design or into optimisation of DSS dynamic response (Disney et al, 2000), the responses shown in Fig. 3 are unlikely to be replicated in the real world. There are at least two important differences, both of which significantly affect system performance. These are:

- Assumption of perfect forecasting
- Assumption of no delays

So to understand something about how performance deteriorates due to these two sources, we have repeated these experiments with exponential smoothing incorporated within the HMMS algorithm. Additionally we have also included a modest production delay between the factory orders being placed and finished goods rolling off the production line and hence accommodate these changes. Due to the modular structure of the block diagram method our z-transform model of the HMMS paint shop scenario enables us to readily update the HMMS model.]

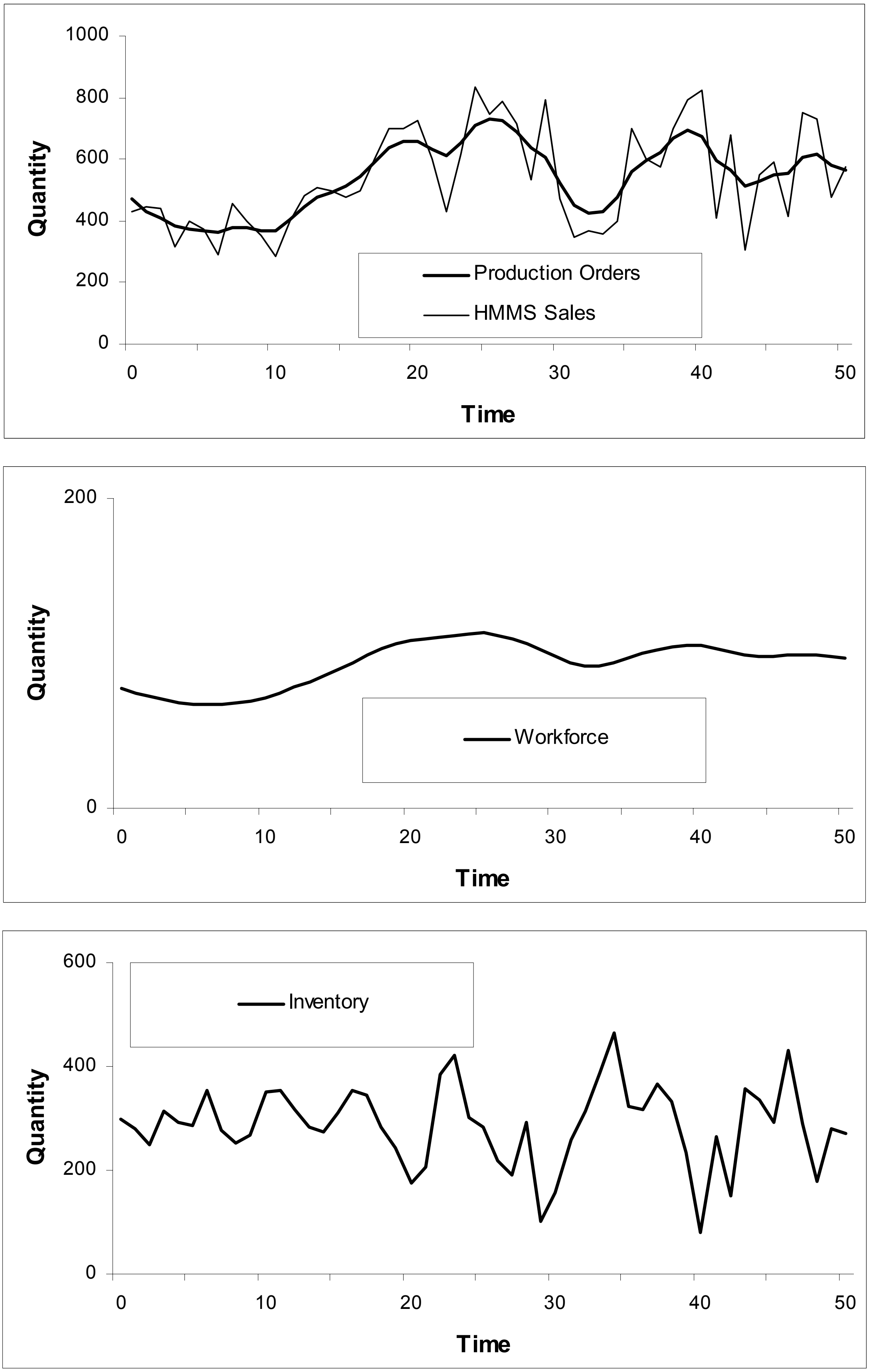


Figure 3. Paint Factory Response in the Ideal World ~ HMMS Rules and Perfect Forecasting (Source: Authors based on Holt et al 1960)

The new time series thus generated are shown in Fig. 4. Compared to the baseline results previously observed in Fig. 3 these relatively small changes to the test scenario have resulted in a substantial deterioration in factory performance. Fortunately the good news is that the workforce Time Series has not been greatly affected by using a realistic forecast and also incorporating a production time delay. But the bad news is that the production orders to the factory are now much more volatile. So although hiring/firing costs have not been greatly affected because the algorithm has damped down workforce fluctuations, overtime and idle time costs will have increased dramatically in order to meet variable production orders. Furthermore inventory swings are now much greater (by a factor of 3:1). Consequently there is a higher degree of overstocking but unfortunately this still does not prevent us entering into a backlog situation.

8. Approximate Dynamic Equivalence of HMMS and APIOBPCS

In this section we shall demonstrate the broad equivalence between HMMS algorithms and the family of Automatic Pipeline, Inventory and Order Based Production Control System (APIOBPCS) ordering algorithms. The latter are well described in Disney, Naim and Towill (2000) and John, Naim and Towill (1994) so there is no need for repetition here. It may be useful, however, to emphasise that APIOBPCS is an established decision rule that utilises information on forecast of future demand, present demand, inventory surplus/shortfall, expected lead-time, and goods in the pipeline. APIOBPCS is thus a generalisation of the algorithm proposed by Popplewell and Bonney (1987). For the purpose of this paper the algorithms are expressed as transfer functions written in terms of the z transform to which the input driving the system is sales. However APIOBPCS can be expressed in words as follows;

"Let the production targets be equal to the sum of: averaged demand (exponentially smoothed over Ta time units), a fraction (1/Ti) of the inventory difference in actual stock compared to target stock and the same fraction (1/Tw) of the difference between target Work In Progress (WIP) and actual WIP".

This generic replenishment rule is particularly powerful as it encompasses:

- the way people actually play the Beer Game, Sterman (1989) and Naim and Towill (1995)
- the capability of representing, via a single transfer function, the Lean, Agile and Leagile (Naylor, Berry and Naim, 1999) supply chains, as demonstrated by Towill, Lambrecht, Disney and Dejonckheere (2001)
- a generalised description of order-up-to policies and many variants thereto, Dejonckheere, Disney, Lambrecht and Towill (2002a)

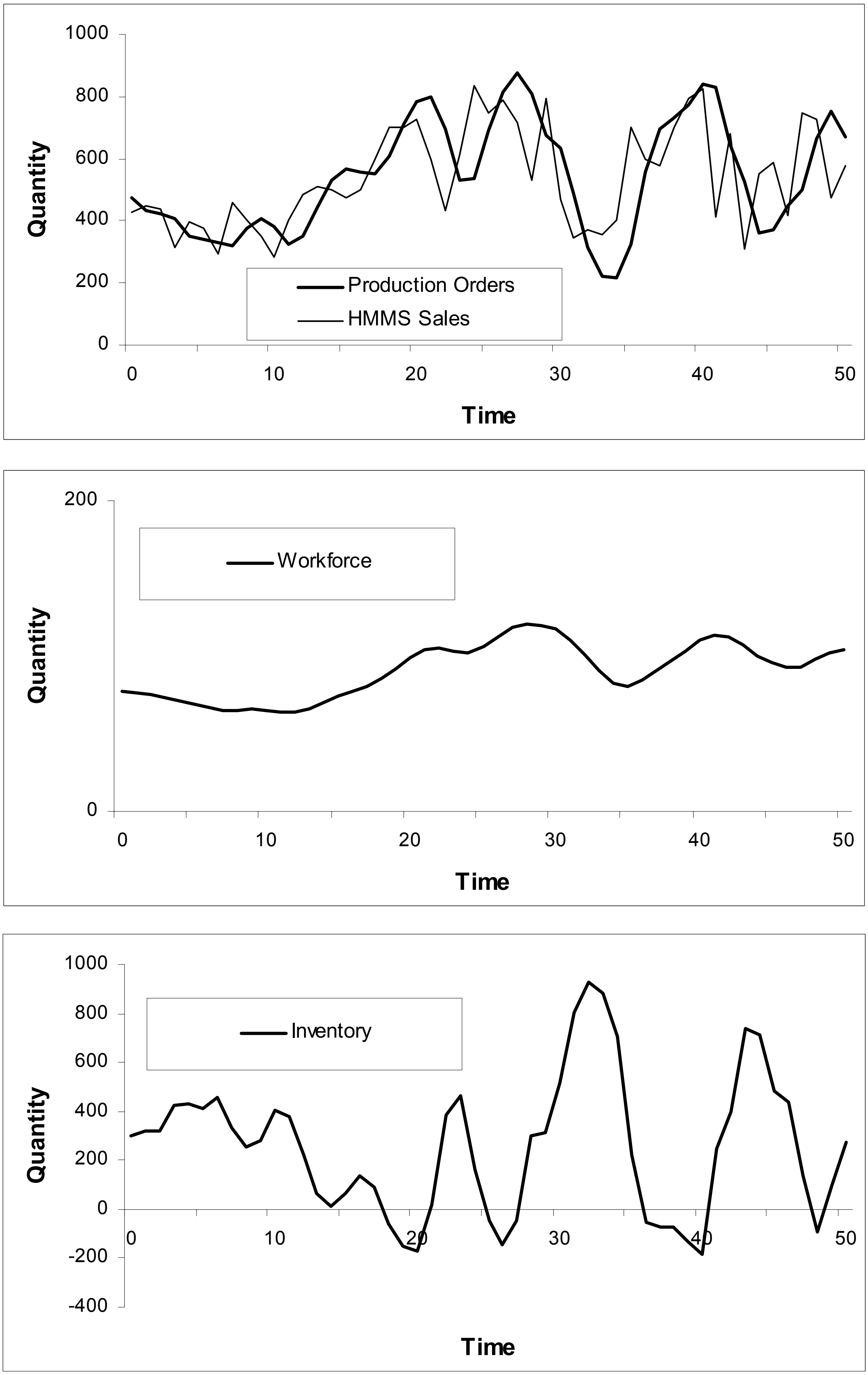


Figure 4. Paint Factory Response ~ Using HMMS algorithm but with Realistic Forecasting Errors and Production Delays to Mimic Real World Conditions

- known industrial usage by many of our industrial partners, as instanced by Evans, Cheema, and Towill, (1997), Olsmats, Edgehill and Towill, (1988), Disney, Holmström, Kaipia and Towill (2001)
- with fine tuning APIOBPCS can reflect Materials Requirements Planning, Disney (2001).

Fig. 5 shows the step responses of both HMMS and APIOBPCS. For HMMS the responses are shown for two cases, that of perfect forecasting and no delays (pure HMMS) and that of realistic forecasting plus a production time delay. Note that with perfect forecasting the system starts responding ***before*** the event. Such behaviour has previously been observed by van Aken (1978) when simulating optimum systems possessing a predictive capability. In contrast the step response of the HMMS algorithm with realistic forecasting plus time delays is markedly different. Most noticeably there is a substantial overshoot (i.e bullwhip), the system takes longer to recover, and, of course the response is initiated ***after*** the step input. In other words, there are real-world problems associated with industrial usage of the HMMS algorithm additional to that of cost function formulation difficulties identified by Buxey (2001).

The time scales associated with HMMS and APIOBPCS are, of course, usually markedly different. HMMS will be concerned with months and years whilst APIOBPCS deals in days and weeks. So to get a realistic comparison between the two we have scaled down the APIOBPCS speed of response to match that of HMMS. For the record, the transfer functions utilised in the simulation are listed in Table 3. Note that the APIOBPCS model selected is not an exact match, but is accurate enough for our purposes. Of course bullwhip can lurk in the background (and often via a bad design in the foreground) of APIOBPCS and is to be constrained via good parameter settings. For the APIOBPCS case shown in Fig. 5 the bullwhip is about 1.30 to 1. Such a value is modest in comparison with that found in many industrial applications (McCullen and Towill, 2001).

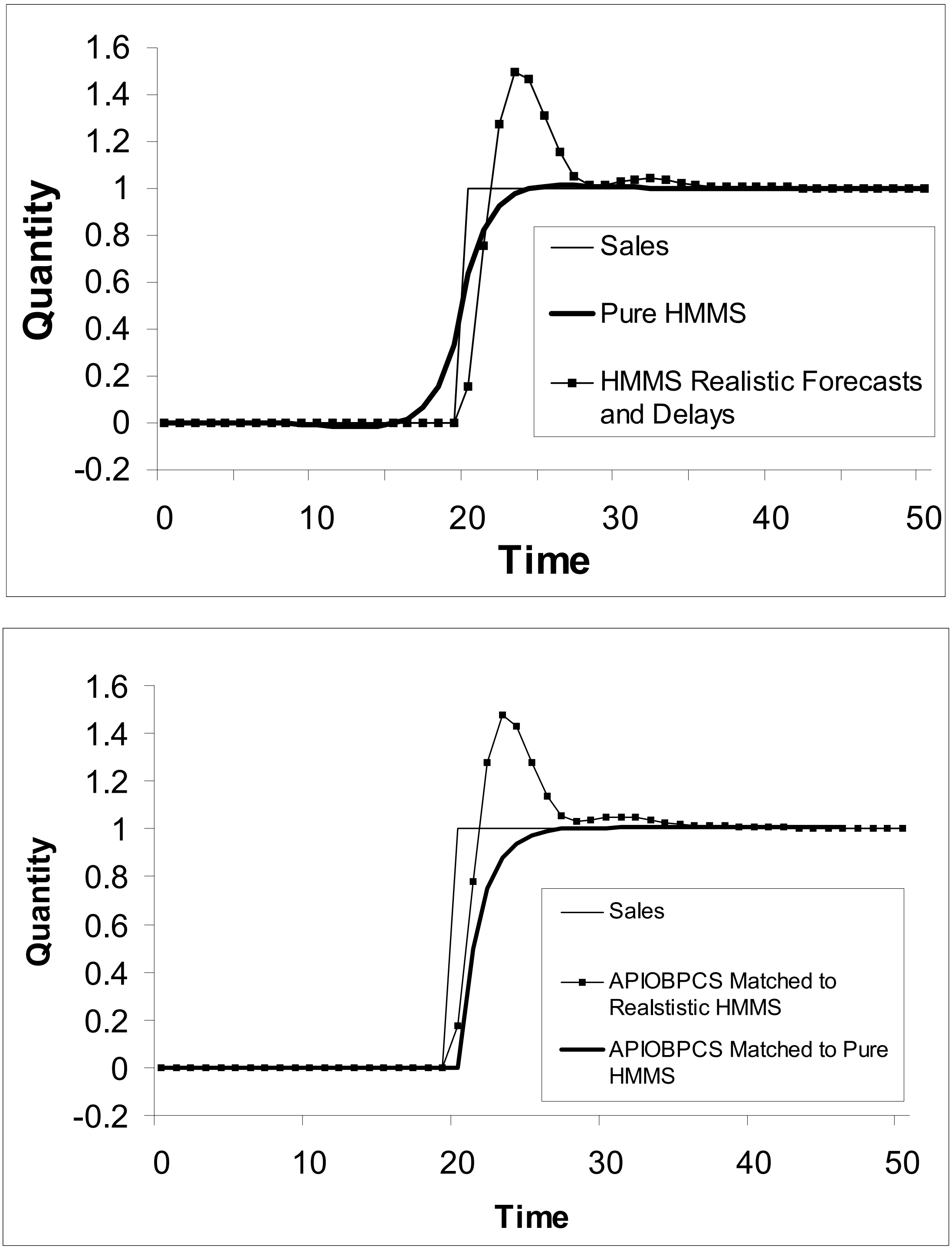


Figure 5. Matching the Models ~ Approximate Dynamic Equivalent Step Responses of HMMS and APIOBPCS Algorithms

9. Does Production Strategy Drive Aggregate Planning?

To attempt to answer the above question Buxey (2001) established current real-world (Australian) aggregate planning practice. This section is based on his survey. His modus operandi was to undertake a study that was made of production planning philosophies at 42 manufacturers known to be experiencing seasonally biased demand. The survey included a wide range of industries and organisations. Each case study involved an interview with a manager(s) followed by a plant tour to make observations and ask further questions. Consequently the discussions encompassed the business environment, strategies for dealing with seasonal variations, the objectives and format of (broad) production planning, resources scheduling, the MPS, shop floor constraints, management issues, and flexibility.

Case	Transfer Function, F(z)
1. Basic HMMS	$-\dfrac{\begin{bmatrix} 0.005(-1.580176+z)(-0.731387+z)(0.153302+z) \\ (2.156359+(-2.284941+z)z)(1.940352+(-0.940581+z)z) \\ (1.813599+z(0.562022+z))(1.792511+z(1.844635+z)) \\ (1.734762+z(2.534824+z)) \end{bmatrix}}{0.408178+(-1.2790+z)z}$
2. HMMS with Realistic Forecasting plus Delays	$\dfrac{(0.791(-0.854+z)(-0.706+z)z(2.807+z))}{((-4+5z)(-0.335+z(1.207+(-1.743+z)z)))}$
3. APIOBPCS Matched to Basic HMMS	$\dfrac{1.027z^2(-0.5937+0.5939z)}{(-1+z)(-0.39+z)(8.078\times10^{-5}+z)}$
4. Typical Operational APIOBPCS	$\dfrac{2.4z^2(-2.30764+2.64443z)}{(-0.8236+z)(0.4579+(-0.9997+z)z)}$

Table 3. Transfer function of (ORATE/SALES) Used to Simulate HMMS and APIOBPCS Matched Model Step Responses

Five strategy options have been inferred from the case study data (level; chase; mixed; demand management; modified chase; other) as defined in Table 4. In his terminology "level production" plan maintains a constant daily production rate, drawing on stockpiles of finished goods whenever factory output dips below the sales mark. Conversely, "chase production" tracks the expected monthly demand pattern by adjusting the direct labour input. The "modified chase" strategy stems from operational constraints that prevent production output tracking the extremities of monthly demand as required in the pure chase mode. The demand management strategy refers to the case where a company tried to influence its sales in some way so as to better match its production capability.

As he makes very clear the companies that feature in the Buxey (2001) survey have no need of complex HMMS algorithms. Instead they review and tailor the form of the MPS to suit their individual circumstances. ***There is no attempt to construct an optimum aggregate plan, let alone convert it into a feasible model-based schedule.*** Typically the unit dollar value to labour cost ratio may vary widely between different SKUs, and product mix generally also fluctuates. Therefore, costs dis-aggregation (preserving the same total labour and inventory cost components) would constitute a Herculean task, compounded, typically, by high product variety. These methodological discrepancies between academic theory and business practise are most obvious when there are discrete summer and winter product ranges to manufacture. In this case the most critical decisions required are the timings of production changeover dates.

A Master Production Schedule (MPS) needs to stretch far enough into the future to facilitate the timely acquisition of labour and raw materials. This does not necessarily mean a full twelve months. Some activities with long lead times (e.g. orders for steel supplies) depend on aggregate forecasts. Later, these act as constraints on the actual MPS used. ***When a straightforward strategy is in place, along with preferred ways to implement it, the entire year does not have to be accounted for in great detail. This greatly simplifies the planning process.*** Initially, product families may be used to construct the MPS. As the relevant time buckets advance closer to the current date more decisions are required and specific product identities evolve. Detailed, model-based sales forecasts are much more accurate and useful at that time. In other words, DSS type algorithms fit these companies better at the SKU ordering level of Fig. 1.

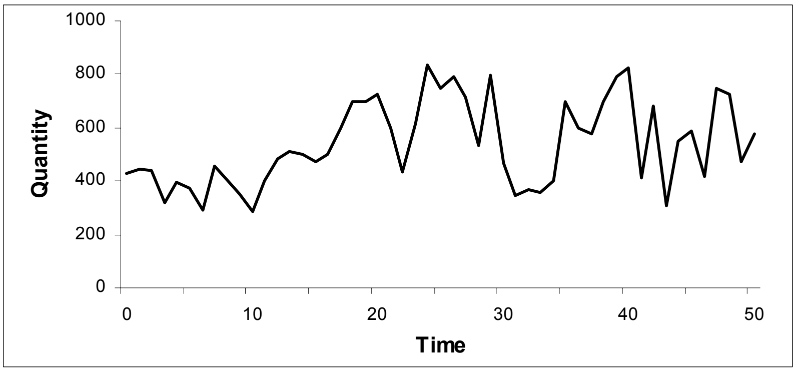
10. Comparing the Paint Factory Responses to Level Scheduling and "Chase" Production Strategies

By starting out with a fixed production-driven strategy, Buxey (2001) concludes that planners are able to delay the commitment of variable resources and the precise definition of products until those moments when lead-times bite and actions have to be taken. They simply follow the general rules that have previously been laid down. It also allows the MPS to be developed from the bottom up, using the degree of detail appropriate for the particular time bucket. The schedule is not then subject to the tight restrictions that are imposed by a more forward looking, "optimal" aggregate plan. Thus, at the level where it counts, the MPS is likely to be reliable, robust and flexible, in contrast to any OR model based alternative that must conform to a lengthy and fixed aggregate plan. We shall now show that the production strategies defined in Table 4 are not in fact in conflict with an algorithmic approach. The value of Table 4 is that it is ***the production strategy that selects the algorithm, not the algorithm output that determines manufacturing policy***.

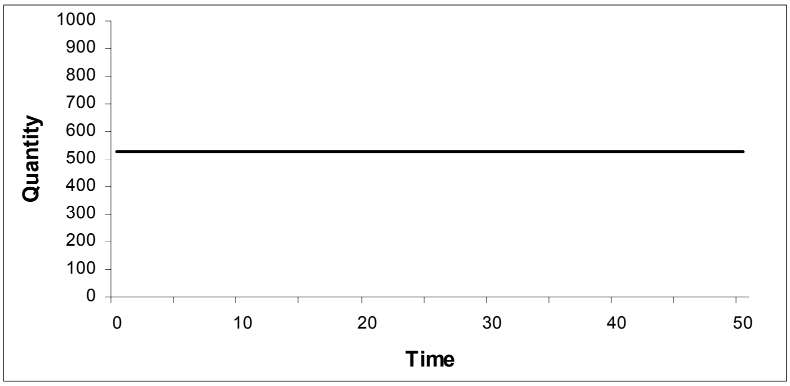
PRODUCTION STRATEGY	TYPICAL OPERATIONAL CHARACTERISTICS
Level Scheduling Strategy (4 Companies)	• Limited variety of stable products with modest seasonality • Demand forecasting is fairly reliable • Little scope for volume flexibility • Marketing specifies the model mix each month • Marketing responsible for selling the annual production output
Chase Strategy (19 Companies)	• Predetermined strategy shapes production schedule • Predetermined strategy plans acquisition of resources • No attempt to balance marginal costs • Strategy means the business suffers minimum financial exposure • Retain enough flexibility to react quickly to seasonal demands
Modified Chase Strategy (12 Companies)	• Practical amendment of chase strategy to track maximum demand • Planners engage in a limited form of stockpiling • Large orders have to be placed on long lead times • Big jobs may be slotted into the MPS earlier than needed • Work transferred from peak periods into slack ones.
Demand Management Strategy (4 Companies)	• This strategy appears the ideal way to tackle the seasonal problem • Strives to develop complementary product range • Two semi-independent production schedules result in a level workload • At facilities change-over adequate stock must be in place
Other Strategies (3 Companies)	• Dominated by labour and learning considerations • Hire and fire policy wasteful; need for stable core workforce • During the high season extensive overtime is scheduled • Only unskilled positions filled by temporary recruits • Limited idle time tolerated off season

Table 4. Real World Planning Scenarios ~Typical Operational Characteristics of Production Strategy Options Evolving from Study of 42 Australian Manufacturers (Based on the description by Buxey, 2001)

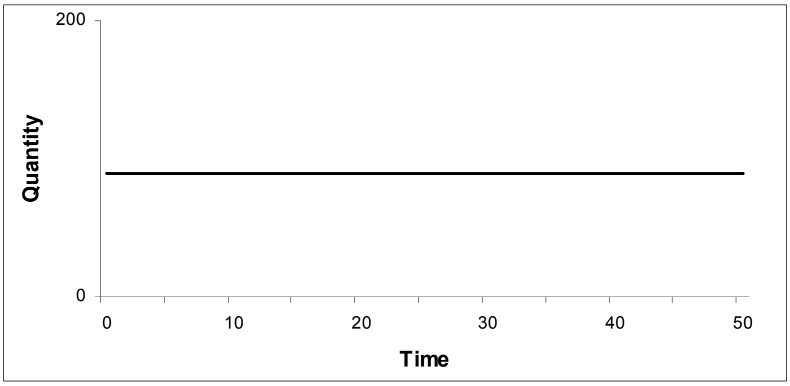
Because we seek a dynamic performance comparison (as distinct from the costs comparison of Table 2) we need to examine how the paint factory might have responded to the "level scheduling" and to the "chase" strategies. Fig. 6 shows the results for the level scheduling case. We have assumed that there is no production lead-time (very unlikely in practice). Hence in reality these results will be optimistic. Both orders placed on the factory and workforce levels are constant. But the downside is the huge build-up in inventory followed by a decline leading to stock-outs.



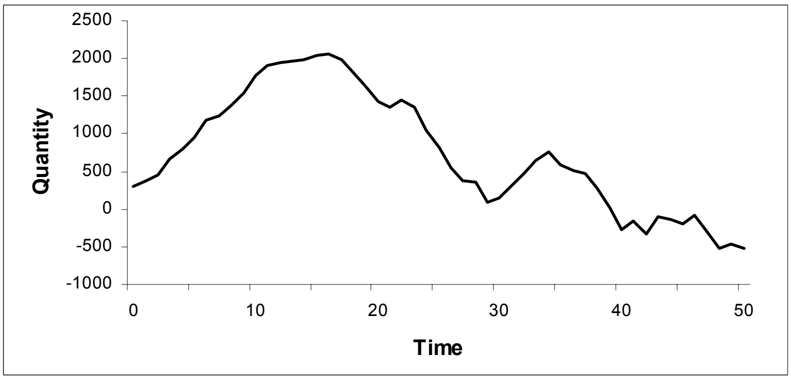
(a) HMMS Sales



(b) Production



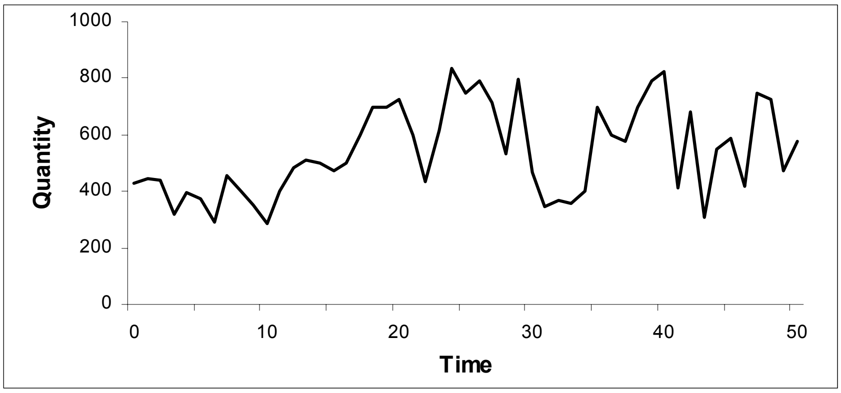
(c) Workforce



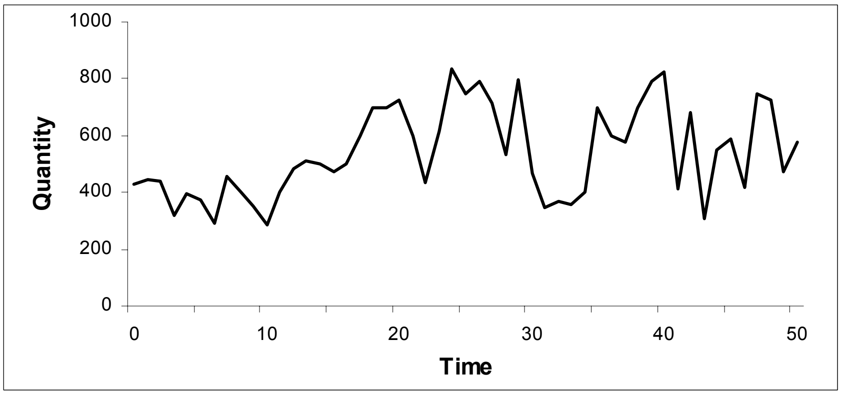
(d) Inventory

Figure 6. Paint Factory Response to "Level Scheduling" Production Strategy

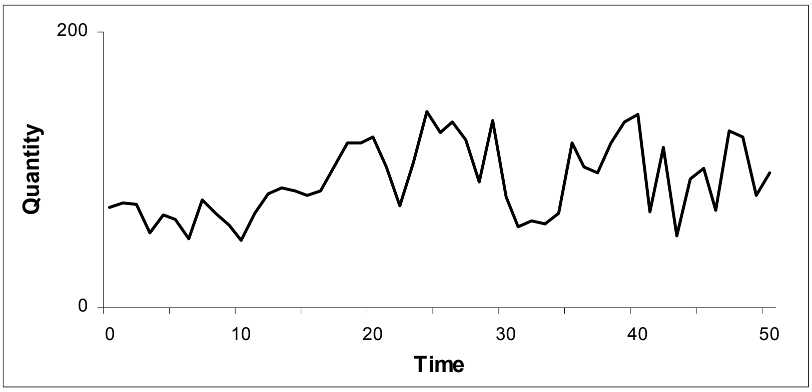
Dejonckheere, J., Disney, S.M., Lambrecht, M.R. and Towill, D.R., (2003), "Dynamics of aggregate planning", Production Planning and Control, Vol. 14, No. 6, pp497–516. DOI: 10.1080/09537280310001621967.



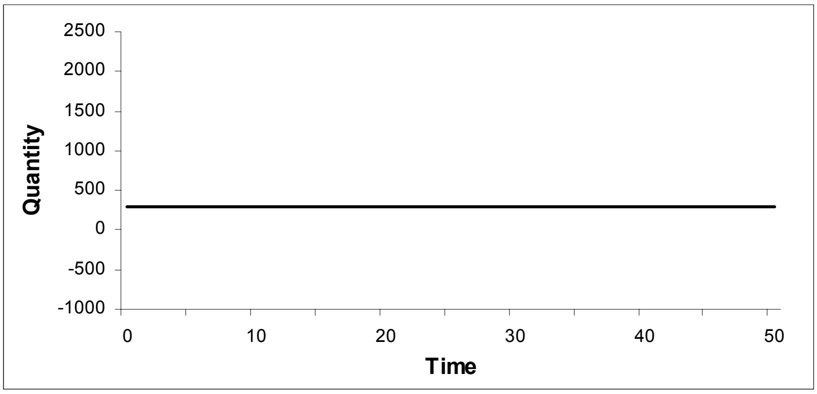
(a) HMMS sales



(b) Production



(c) Workforce



(d) Inventory

Figure 7. Paint Factory Response to "Chase" Production Strategy

Fig. 7 shows the corresponding paint factory response to implementation of the "chase" production strategy. Sales are passed directly as factory orders with no filtering whatsoever. To produce according to schedule, capacity must be ramped up and down in unison with factory orders. Our simulation assumes that there are no capacity constraints, and even more importantly there are no lags in take-up and release of capacity. In other words, spare workforce, machines, and materials are available and 100% effective on tap with no start-up problems. Hence again our results are optimistic. The resulting wild (and very sharp-edged) changes in workforce would be very difficult to cope with. In the real world inventory levels would, of necessity, fluctuate in meeting shortfalls and surpluses caused by imperfect capacity and production responses.

Table 5 summarises the paint factory responses under the conditions of HMMS; "realistic" HMMS; level scheduling; and "chase" production strategies. The results have been quoted in terms of the range about mean levels. This yields a performance metric extremely easy to visualise and compare. It is now not only clear what the various trade-offs are, but also their magnitude. For example, the "chase" strategy requires workforce swings twice that predicted by HMMS and are significantly more frequent. But as compensation we do not then run the risk of obsolescent stock.

Case No.	Aggregate Planning Policy	Swings in Orders to Factory	Swings in Workforce	Swings in Inventory	Comments
1	**HMMS Optimum (perfect forecast and no delays)**	**± 181**	**± 23.5**	**± 194**	"Ideal" Response Chosen as initial benchmark
2	**HMMS (Delays plus realistic forecast)**	**± 322**	**± 27.5**	**± 562.5**	Realistic operating conditions significantly and negatively impact Factory Orders and Inventory
3	**Level Scheduling (No delays)**	**± 0**	**± 0**	**± 1300**	Huge inventory requirement
4	**Chase Pursuit (No delays)**	**± 280**	**± 45**	**± 0**	Huge capacity swings probably leading to hire-fire workforce policy

Table 5. Summary of Dynamic Response of Various Competitive Aggregate Planning Policies to Paint Factory Sales Data

11. Filter Properties of Competing Aggregate Planning Systems

It is not necessary to perform endless simulations to fully understand the important properties of aggregate planning systems. Instead, via the filter approach the frequency response profile may be used to predict behaviour under a wide range of circumstances. So we have computed the frequency responses for the HMMS and HMMS with realistic forecasting and time delays directly from their transfer functions. The results are shown in Fig. 8 for factory orders; workforce levels; and inventory all for assumed sinusoidal sales variations. Also shown are the frequency responses for the level scheduling and "chase" production strategies. For the case of zero lead times these may be written down by inspection.

As we have already seen from the paint factory simulations, since level scheduling ignores sales data, it has a frequency response of zero (meaning no acknowledgement of variability of demand) for both factory orders and workforce. In contrast the response for inventory is unity at all frequencies, which means that all sales fluctuations are passed straight through to inventory. In theory the "chase" production strategy is the converse of level scheduling. Factory orders and workforce levels have no buffering so hence their response is expected to be unity at all frequencies. Every ripple in the marketplace must be responded to by the factory, with inventory being held to a minimum (in theory, zero).

These responses may be even better understood by sketching out the individual waveforms at particular spot frequencies. In particular the significance of amplitude ratios greater than one, and less than one, will become much more apparent. The requisite amplitudes may be determined directly by inspecting the plots shown in Fig. 8. For illustrative purposes the spot frequency we have selected corresponds to (-2) on the 10 $\log_{10}$ scale. It is readily shown for the paint factory Case Study that this is equivalent to a waveform with a period of 10 months.

The spot frequency results are shown in Fig. 9. Note that as expected the "realistic" HMMS algorithm demonstrates substantial demand amplification (bullwhip) on the Order rate waveform. On Workforce the "realistic" HMMS does not attenuate fluctuations as well as the "ideal" HMMS. Thus although the "swings" in Workforce listed in Table 4 are not much worse than for the "pure" HMMS algorithm, there is distinctly more sinusoidal activity at most frequencies. This explains why there are more ripples in the Workforce response to the sales data as shown in Fig. 4 compared to Fig. 3. The practical implication to the manager having to face up to is more volatility in hire/fire decision-making.

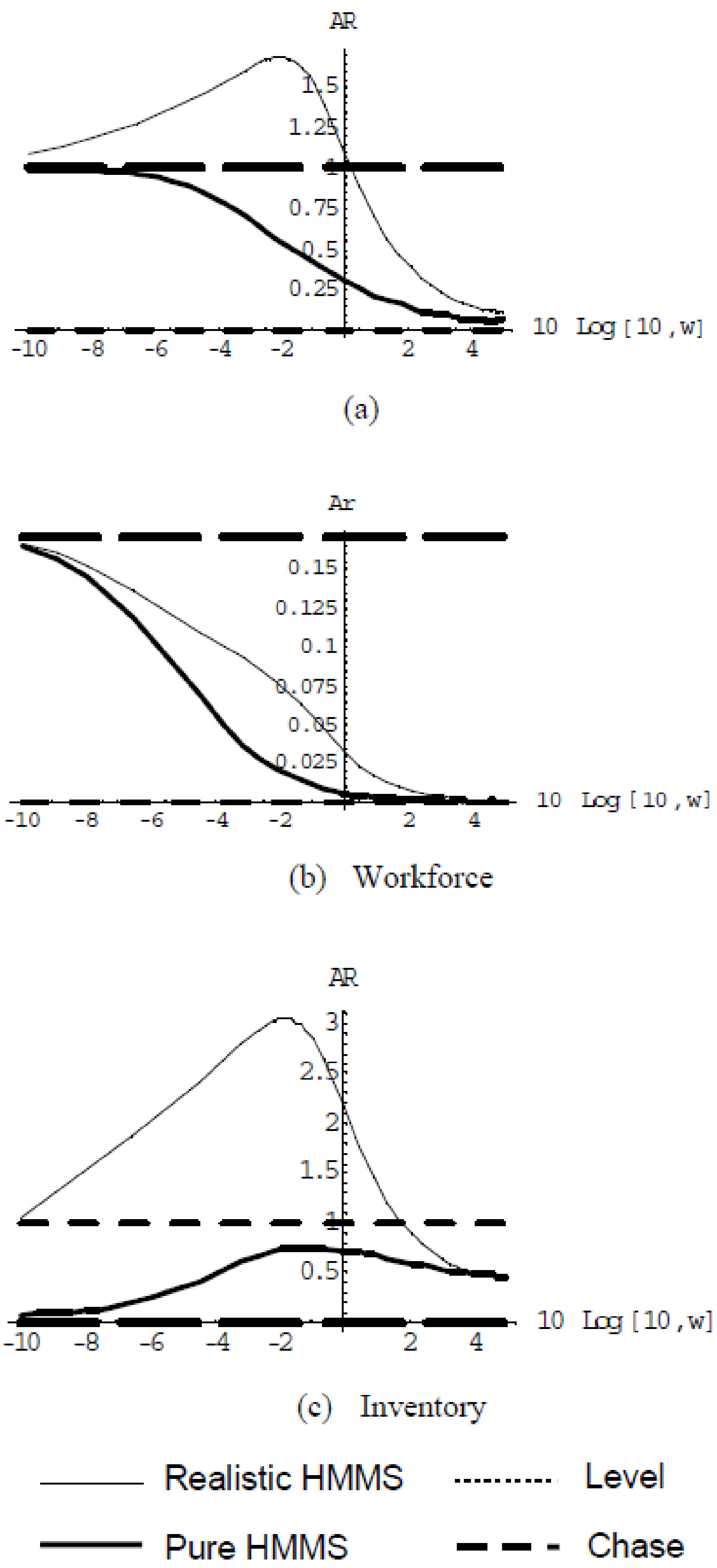


Figure 8. Frequency Response Amplitude Plots for Competing Aggregate Planning Systems of Table 5

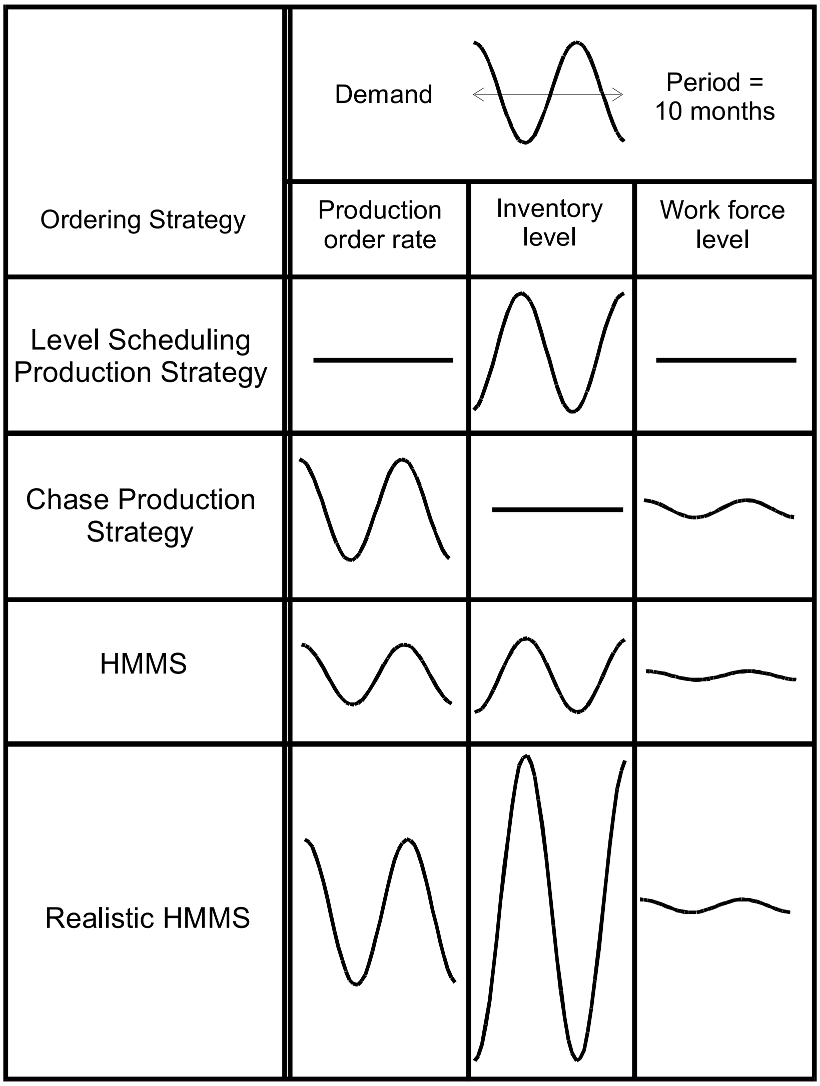


Figure 9. Developing Insight ~ Spot Frequency Responses for Competing Aggregate Planning Systems of Table 5

12. Practical Impact of Filter Theory on Aggregate Planning

To further relate the Ideal Filter to Practical Aggregate Planning we have constructed the idealised frequency responses at two spot frequencies. One of these has been selected in the "message" region, i.e. below the cut-off frequency, and where we wish to track genuine demand variation. The second is above the cut-off frequency. This is where the volatility is assumed to be unwanted "noise" and is to be filtered out. Fig. 10 shows the expected behaviour at these two spot frequencies for the following strategies:

- Level Scheduling
- "Chase"
- Ideal Filter
- Practical Filter (good design: well selected coefficients)
- Practical Filter (indifferent design: arbitrarily selected coefficients)

The trade-offs between the various strategies is self-evident from the visual displays of Fig. 10.

We have included two examples of practical filters. In the first instance we assume it is well designed, and in the second instance an indifferent design with arbitrary coefficients. The reason is that we have included both in that we have often found industrialists using the right algorithms but with inappropriate parameter settings. The algorithm is usually blamed for bad results that are really due to poor setting-up procedures. A real world example of such a scenario is given in Evans, Cheema, and Towill, (1997). Users of such algorithms must understand the need to “tune” them to suit both their operating circumstances (lead times etc) and the production strategy of the business. In such a situation it helps management to decided on the appropriate strategy if the right data is available, for example flow curves of important variables such as sales, orders, and inventory levels (Gianesin and Pozzan, 2000). The latter authors imply what we have now shown, that such algorithms can be very simple. Once properly installed they will deliver under specified conditions exactly as the designer intended (John, Naim, and Towill, 1994).

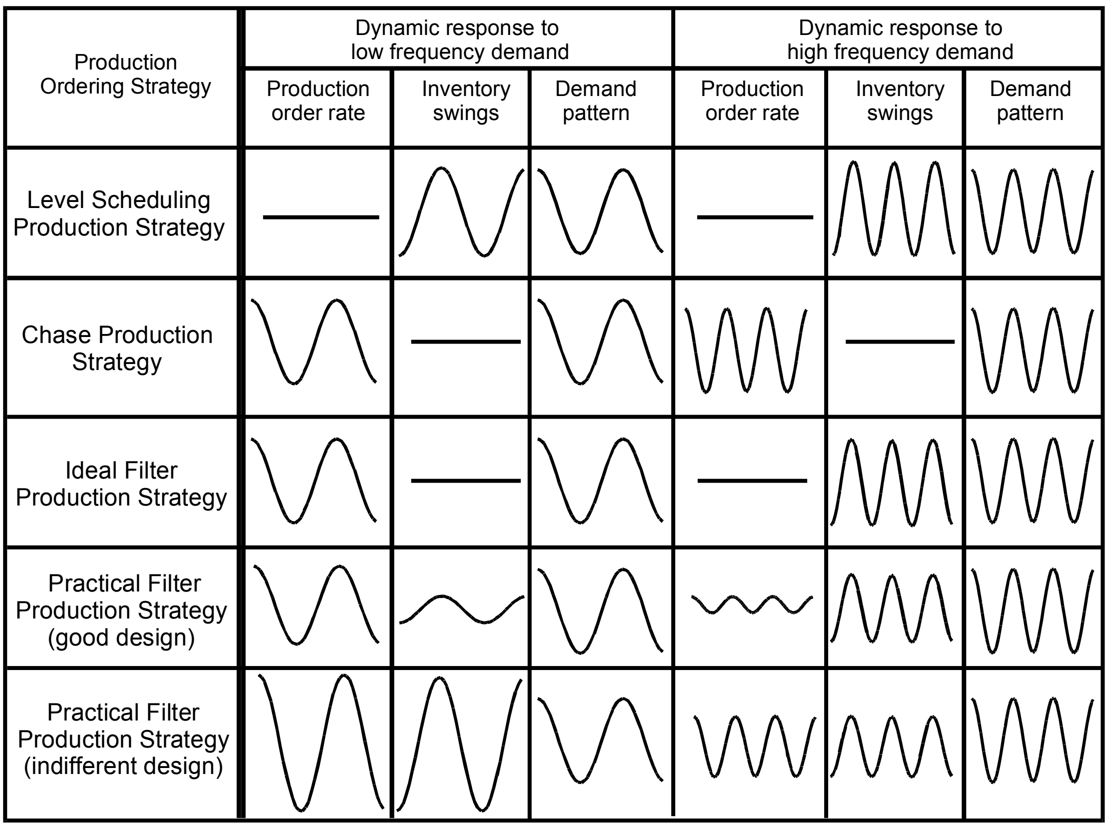


Fig. 10. Generalised Application of Filter Concept to Aggregate Planning

13. Implications and Results

It is now obvious that the “Ideal filter” could be enabled, in theory, by a suitable combination of “chase” and “level scheduling” strategies. For example, for the companies classified in Table 4 as practising the Demand Management Strategy, seasonality can be tackled by moving from "chase" to "level scheduling" at specific points in time. For example, the National Bicycle Company practises "chase" during the summer when it makes special sports cycles to order. During the autumn it switches to "level scheduling" production by stockpiling standard models. These sell throughout the year. The following spring production is switched back to the "chase" mode ready for the new sports season (Fisher, 1997). As the listed operational characteristics of Demand Management make clear, it is essential that at switching times the facilities available and stock levels must be matched to needs.

Can we generalise the results in this paper and bring together real-world production strategy, filter theory, and the exploitation of simple APIOBPCS type software to provide a set of user Guidelines? Table 6 attempts to satisfy this need. The "equivalent filter" for each strategy is listed. Also shown is our view on whether the algorithm potential for dynamic aggregate planing may be regarded as high or low. The typical algorithmic applications include trend detection, capacity smoothing, and full dynamic control. Note that there is apparently no need to use such a complex algorithm as HMMS. As we have many times demonstrated in this paper (for example in Fig. 5/Table3), if the user states his requirements on a simple filtering basis, an adequate form of APIOBPCS can be matched to the operating scenario. This satisfies the perceived industrial need for simple, robust, production control systems (Monniot et al, 1987), and for the call by Solberg, (1992) that they should be judged on the grounds of validity, credibility and generality.

14. Conclusions and a Way Forward

It may well be that there are many businesses where the use of HMMS type algorithms is justified. But there is a major difficulty in establishing a satisfactory cost model against which the optimisation may proceed. There are also associated problems of dis-aggregation when exploding down BOM levels etc. from the so-called optimum aggregate solution. It may also be argued that the formulation of the model and interpretation of results is also difficult when viewed from an operations management perspective. Also, we have demonstrated herein that if the prime requirement is to smooth either historical data, or to simulate an assumed test case (as a baseline for future planning) then a simple filter will do this job just as well.

A likely explanation of the results obtained in the extensive survey of Australian businesses by Buxey (2001) lies in a quotation by Karl Popper (Engelbrecht, 2000). He said "there are many circumstances where it is much better to be vaguely right than precisely wrong". This feeling will be echoed by many executives concerned with aggregate planning. As we have seen in Fig. 1 it is much more likely that precision is needed at Level 3 (how many of which SKU's do we make today?) and Level 4 (how do we deliver these factory orders?). At the Aggregate Planning Level, Filter Theory clearly has a role to play, since it obviously relates to practical production strategy.

Present Production Strategy	**"Equivalent Filter" as applied to sales orders**	**Potential for Algorithmic Planning and Control**	**Typical Algorithmic Application**
Level Scheduling	"No Pass"	Low	Use APIOBPCS to monitor the long term mean and detect trends
Chase	"All Pass"	Low	Use APIOBPCS to track sales and smooth extreme capacity swings
Modified Chase	"Low Pass Filter"	High	Scope for tailoring APIOBPCS to specific business strategies
Demand Management	Mimics "Ideal Filter"	Low	Use APIOBPCS for trend detection and capacity smoothing
Other	"Low Pass Filter"	High	Scope for extending APIOBPCS to include learning curves

Table 6. The Relationship Between Production Strategy, Filter Equivalence, and Potential Exploitation of APIOBPCS software

But in terms of interacting with operations managers, it is not necessary to expound the theory. It is the practical implementation of the "ideal filter" via the APIOBPCS algorithm that counts. Managers have generally some understanding of real-world frequency separation on which to build such an analogy. Loudspeaker systems and car suspension systems are but two relevant examples from everyday life to draw upon. The fact that level scheduling and "chase" production strategies are at opposing ends of the frequency spectrum naturally begs the question as to when simple solutions at some intermediate operating point are advantageous. Both Fisher (1997) and Towill and Christopher (2001) provide some useful insights here, especially on how "chase" and "level scheduling" may be optimally combined to best respond to "real" market demand, thus minimising the "ideal" filter.

So we may summarise a possible way forward as shown in Fig. 11. Note that Filter Theory can easily become as complex as the OR Approach. In fact the mathematical optimisation of filters has a long and distinguished history dating at least as far back to Lee (1967). But as with HMMS there is little need for formal optimisation if simple equivalent filters are available to perform the task. Our argument is that operations managers are able, and need to be encouraged, to think of marketplace volatility in dynamic terms, for which frequency domain is the most initiative. The input from any analyst should then be restricted to recommending and testing simple software capable of satisfying management situations over a wide range of operating scenarios. Of course the simpler the solution the better. One practical way of improving performance is to combine filtering with level scheduling, in which the capacity level is switched at times predicted by the filter output. In other words we can convert the arbitrarily switched production level scheme proposed by Suzaki (1987) into a dynamic self-adaptive system with the need for transition between levels being triggered by an appropriate function of sales. This could be calculated via an APIOBPCS type Decision Support System.

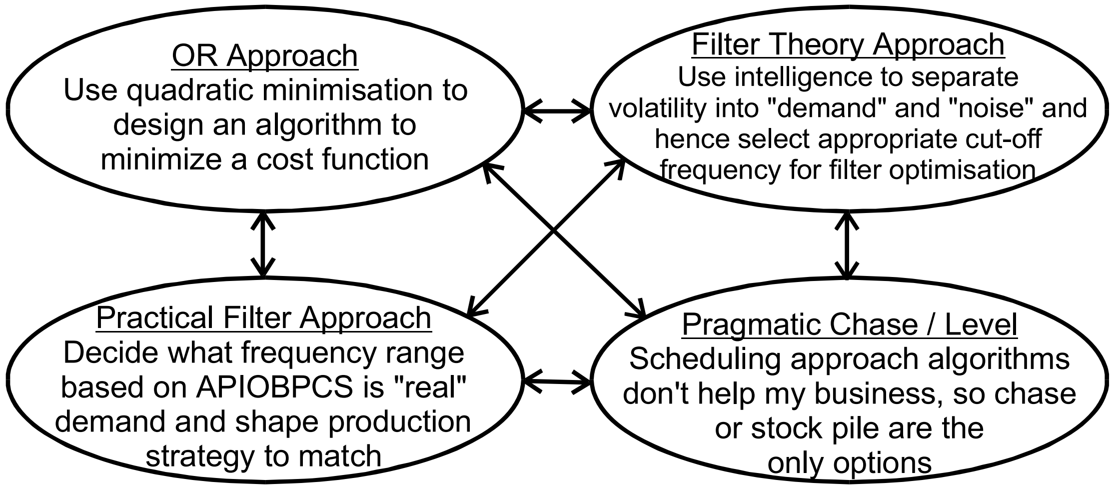


Figure 11. Summary of Four Ways of Dealing with the Aggregate Planning Problem

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