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Analytical Planning Stability Research: No Reason for Nervousness!

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Analytical Planning Stability Research: No Reason for Nervousness![1]

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1 Introduction

Planning stability or its counterpart, planning nervousness, is a challenging issue for many companies as well as for scientists who try to analyze and explain this phenomenon. It was, however, not just this topic that stood at the beginning of the collaboration between Ton de Kok and me. We both spent some time of practical work with a company before we started our university careers. In practice, we both were confronted with challenging problems from the field of supply chain planning which we made to a central subject of our scientific work after switching to academia. This common interest in supply chain optimization brought us together, and it is this area where one of our two joint papers (Inderfurth et al. (2001)) refers to.

The other publication (De Kok and Inderfurth (1997)) belongs to a different field and considers the issue that this paper is dedicated to, namely the analysis of nervousness in planning systems. The problem is old, but research in this area for a long time was only descriptive or simulation-based. This changed in the middle 1990s when the first analytical investigation was published in Inderfurth (1994). In this context, I was happy that I could draw Ton's attention to this research topic so that a collaboration started in which I could profit a lot from Ton's enormous analytic expertise. Starting with this joint research, the present paper presents an overview of the outcome of the analytical research contributions on the topic of planning stability. It describes the advantages of gaining analytical insights, but also the technical difficulties of this research approach which might have deterred many researchers from trying to analyze planning stability in this way. A matter of nervousness in tackling hard problems?

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[1] This paper is a contribution to a Liber Amicorum for Prof. Dr. Ton de Kok from the Eindhoven of Technology

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2 Planning Stability Research

Research in the area of planning stability mainly concentrates on the field of production and materials planning. Standard planning systems like MRP are generally operating in a rolling horizon framework where after each period a replanning takes place according to updated information. Updates, in general, stem from a prolongation of the planning horizon and from forecast errors and new demand estimates. Thus, changes in the quantity or timing of planned orders are generated which create system nervousness. Planning stability research focusses on how MRP rules and policies affect the size of planning instability. In practice, different types of Period Order Quantity (POQ) or Fixed Order Quantity (FOQ) lotsizing are used in an MRP context. Under demand uncertainty these lotsizing policies are equivalent to employing stochastic inventory control rules of the *(s,nQ)*, *(s,S)*, or *(R,S)* type (see Lagodimos and Anderson (1993)). Therefore, much research concerning planning nervousness refers to the impact of these rules and their parameters.

Usually, in the field of production and inventory planning the economic effect of different control rules is measured in terms of operating cost. In many cases, however, a pure cost-oriented valuation of effects is not sufficient so that an additional measure is needed. This is well-known for the objective of reaching a high service degree. If cost of material shortages can hardly be estimated, a service level is used as an additional criterion to assess the performance of a planning system. Next to service deficiencies, frequent replanning activities can harm the efficiency of planning procedures. In general, the impact of planning nervousness is much harder to value in terms of costs than the service impact. So, the level of planning stability can be viewed as the third attribute that, next to cost and service level, is a relevant performance criterion of a planning system. Accordingly, almost all scientific contributions in the field address the influence of ordering rules on the stability level isolated from cost considerations.

The majority of research papers which investigate the impact of control rules on system nervousness is based on simulation methods. This starts with a first study by Blackburn et al. (1986) and continues to recent papers like those by Atadeniz and Sridharan (2020) and Sáez et al. (2023). Many of these papers consider the impact of different standard planning procedures, others are dedicated to the analysis of specific planning tools which are designed for dampening planning instability. Simulation-based studies can cope with complex planning situations met in multi-product, multi-stage production systems or with different kinds of stochastic inputs and non-stationarities. These research contributions also allow for an analysis of the impact of various dampening methods on planning nervousness. They, however, are bound to a specific planning environment and do not allow for deeper and general insights into the interrelationship between specific control rules and the degree of planning instability generated by them. Additionally, these approaches typically use problem-specific measures for the size of planning nervousness which cannot be generalized. Thus, a comparison of the nervousness level under different planning scenarios is not possible.

To overcome the shortcomings of these simulation-based procedures analytical approaches have been developed. For sake of mathematical tractability, they mainly are restricted to planning problems with a single-item, single-stage environment and to the application of basic inventory control rules. Despite these limitations they provide important insights into the creation of nervousness. These analytical approaches and their general findings will be described in the sequel.

3 Analytical Approaches

In all analytical approaches under consideration the main inventory control rules, namely the *(s,nQ)*, *(s,S)*, and *(R,S)* rule, are investigated under stochastic demand conditions. Completely different from standard stochastic inventory research which aims to find optimal control parameters for a single planning instance, nervousness research analyzes steady state conditions of two consecutive planning runs and compares ordering decisions for the same planning periods in these runs. By this way it is possible to develop closed-form formulas which describe how the level of planning nervousness in form of order deviations depends on the choice of the specific control rule and its parameters.

In order to investigate the interdependence of consecutive planning instances analytically, usually some restrictions concerning the planning situation must be accepted. Only single-stage stationary inventory systems with stochastic demand and an infinite planning horizon are considered. The demand per period is assumed to be a stationary and independent random variable. The demand's expected value is used as (constant) demand forecast (denoted by *D*) for each planning period of a cycle. Thus, order changes for the same period from cycle to cycle are generated by deviations of the actual demand in the first period from its forecast the period before.

In the literature, we only find a very limited number of contributions which are dedicated to the described type of analysis. Chronologically, these are Inderfurth (1994), De Kok and Inderfurth (1997), Heisig (1998), Heisig and Fleischmann (2001), and Heisig (2002). These approaches differ with respect to the types of order deviations and number of compared planning periods they consider. Depending on the practical relevance of order changes for planning stability, it can be the pure deviation in order quantity from one planning run to the next that matters or, alternatively, the fact that irrespective of the quantity the setup characteristic of orders is changing. Accordingly, we differentiate the types of *quantity-oriented* and *setup-oriented* planning stability. In a temporal respect, only order deviations concerning the first period of a planning horizon might be relevant in practice so that it is *short-term* stability of orders that matters. If multiple periods play a role in the valuation and measurement of order deviations we refer to *long-term* stability.

Thus, in combination we end up with four types of stability cases which reflect the major aspects of nervousness in practical problems. For the sake of comparability of nervousness levels under different problem data and under different control rules, additionally a normalization of the nervousness metric is needed. This aspect is first discussed in Jensen (1993) where a normalized measure is defined in which the size of order deviations under concern is divided by the respective maximum deviation that can occur. In that way, all of the four stability measures introduced above are normalized such that they can only take on numerical values between 0 (minimum stability) and 1 (maximum stability). This is very similar to the normalization of service measures in inventory control where respective service levels (of different types) are limited to an interval between 0 and 1. Concerning these planning stability measures, the five literature contributions with analytical stability research present deep insights into the planning stability characteristics of the three control rules under consideration.

4 Findings

4.1 Overall Findings

The first finding refers to the impact of the specific control rule parameter which is mainly responsible for the service level that a rule provides. This is the reorder point *s* for the (*s,nQ*) and the (*s,S*) rule, and the reorder level *S* for the (*R,S*) rule. It turns out that these rule parameters have no impact on planning nervousness at all. This holds for both *short-term* and *long-term* planning stability instances. This property can easily be evaluated. It is due to the fact that the respective control parameters in steady state do not influence the sequence and size of order decisions. They only determine the basic inventory level of the production system. Thus, as a general finding we can secure that optimizing customer service and planning stability are no conflicting goals in this planning context.
With respect to the impact of the other control rule parameters, we must consider the specific rules and differ between *short-term* and *long-term* stability.

4.2 Short-term Stability

When applying an (*s,nQ*) policy, planning nervousness is only affected by the size of the standard lotsize *Q*. In De Kok and Inderfurth (1997) it is shown how the level of planning stability π depends on the choice of parameter *Q*. A closed-form solution for the so-called stability function $\pi(Q)$ is derived which can be exploited both analytically and numerically.

Starting with the results for *setup-oriented* stability, it turns out that this measure approaches 100% when the lotsize tends to be very small ($Q \to 0$) or very large ($Q \to \infty$). This result is intuitive. For $Q \to 0$ the (*s,nQ*) policy turns into a simple order-up-to-*s* policy which results in a planned and executed setup in each period of any planning cycle. On the other hand, also for $Q \rightarrow \infty$ more and more planned and executed orders within a cycle become equal because of an increasing number of periods without any setup. Inside these boundaries, $\pi(Q)$ reacts such that the planning stability is quickly decreasing when Q increases until π reaches a minimum level in the region $D \leq Q \leq 2 \cdot D$ Thus, the size of the lotsize/demand ratio is responsible for the instance of maximum planning nervousness. When Q rises further on, planning stability π increases again. The detailed shape of this unimodal stability function as well as the location of its minimum and the respective stability level depend on the properties of the stochastic demand distribution. If a very general distribution function in form of a mixture of two Erlang distributions is chosen, the values of $\pi(Q)$ can be determined numerically for various parameters of the demand distribution. A respective investigation in De Kok and Inderfurth (1997) shows that – as can be expected – the demand variance has a significant impact on the course of $\pi(Q)$. It appears that for all values of Q the level of nervousness increases if demand variability rises. To get an idea of the numerical value of the stability measure, the π value will be reported for the specific lotsize Q which triggers minimum planning stability. In this case, the size of the stability level goes down to 57% if the squared coefficient of demand variation (*CV*) is very high (*CV*=2.0) and reaches 87% for low variation (*CV*=0.25).

The respective property of the stability function $\pi(Q)$ is very different if we consider *quantity-oriented* planning stability. When deviations in the complete order quantity matter, a 100% stability cannot be reached under random demand. Surprisingly, however, this type of stability does not change with a variation of lotsize Q. The stability level only depends on the properties of the demand distribution and, specifically, on the demand variability. With respect to the *CV* impact, its size is close to the values reported above for the minimum level for *setup-oriented* stability. The main finding from this analysis is that *quantity-oriented* stability cannot be controlled by parameter choice under an (*s,nQ*) policy.

When an (*s,S*) rule is applied, an analogous analysis of ordering-related nervousness can be performed. Here, we find closed-form expressions for a stability function $\pi(Q_M)$ which describes how stability measure π depends on minimum lotsize Q_M (with $Q_M = S - s$). So, under the (*s,S*) rule the lotsize parameter is defined by the spread between reorder level and reorder point. For *setup-oriented* stability the same property of 100% stability holds for the lotsize limits $Q_M \to 0$ and $Q_M \to \infty$ like under the (*s,nQ*) policy. Concerning the complete course of stability function $\pi(Q_M)$, a different picture emerges. Starting from the 100% level at $Q_M \to 0$, stability π sharply declines with increasing Q_M and reaches its minimum value exactly at $Q_M = D$. A further rise of Q_M results in an upward jump of stability π followed by a monotone increase. Thus, as a specific property of the stability function for an (*s,S*) policy we find that a discontinuity appears at a lotsize level which equals the demand forecast. At this order size, which represents a lot-for-lot policy we face minimum planning stability with values of only 45% for demand variability *CD*=2.0 and 61% for *CD*=0.25.

When we turn to *quantity-oriented* stability, we find that the stability function in the case of an (*s,S*) policy shows a behavior that is very different from the one under an (*s,nQ*) rule. Only for the lotsize limits $Q_M = Q \to 0$ and $Q_M = Q \to \infty$ the stability values for both control rules coincide. Under an (*s,S*) policy, however, the stability level π does not remain constant for varying lotsize choices. Instead, stability always undershoots the (*s,nQ*) level. The respective stability function has properties similar to those in the case of *setup-oriented* stability. That means that we find a discontinuity at the lotsize level $Q_M = D$ which also characterizes the location of minimum planning stability.

Different from the situation under reorder-point control rules, the analysis of planning stability under an (*R,S*) policy turns out to be quite simple. Because the replenishment cycle has a fixed length of *R* periods, every cycle starts with an order-up-to-*S* decision followed by *R*-1 periods of zero setups. This holds for the same periods in consecutive planning runs. Thus, the sequence of respective setups is identical, resulting in a 100% *setup-oriented* planning stability (given that zero demand cannot occur with positive probability). With respect to *quantity-oriented* stability it is obvious that in the first period of a cycle a deviation between planned and executed order will emerge. On average this difference amounts to the mean absolute deviation of demand from its expectation (=forecast). For *R*=1 the (*R,S*) policy simplifies to an ordinary order-up-to-*S* rule just like we found for the reorder-point policies in the case of $Q_M = Q \to 0$. So the *quantity-oriented* stability level in this special (*R,S*) case is below 100% and is identical to respective value for the (*s,nQ*) and (*s,S*) policy with $Q_M = Q \to 0$.

For larger reorder cycles (*R*>1) the planning stability increases due to more and more identical non-setup periods and approaches 100% for $R \to \infty$.

A comparison of the three control policies shows that with respect to planning stability the periodic (*R,S*) rule is always superior to the reorder-point policies. Referring to the stability properties of (*s,nQ*) and (*s,S*) rule, a clear dominance does not exist. If we compare the stability results for varying lotsize parameters $Q=Q_M$ we can observe that the *setup-oriented* stability is higher for the (*s,nQ*) policy if $Q=Q_M \leq D$, but higher for the (*s,S*) policy if $Q=Q_M > 2 \cdot D$. In between this lot parameter interval, the relative superiority depends on the variability level of demand. When we consider *quantity-oriented* stability, analytical results for a direct comparison are only available for the range $Q=Q_M \leq D$. Here it turns out that, like for the *setup-oriented* measure, the (*s,nQ*) policy guarantees a higher planning stability than the (*s,S*) rule. From numerical investigations there is some evidence that this superiority of the (*s,nQ*) rule holds for the complete domain of lotsize values.

4.3 Long-term Stability

Long-term planning stability refers to a situation where order deviations over multiple periods of a planning horizon play a significant role in the context of nervousness. In this case, an appropriate measure of planning stability must include additional information. First, the number of planning periods has to be determined for which deviations are of relevance. Here, this number will be introduced as stability horizon, denoted by *T*. Second, it must be considered how order deviations in different periods should be weighted for an overall stability metric. Subsequently, it is assumed that all periods are weighted equally.

In De Kok and Inderfurth (1997) it can be found that the analytical derivation of the stability functions for the *short-term* stability case needs a huge amount of cumbersome algebra. In the *long-term* stability context, complete sequences of *T* orders have to be compared and analyzed with respect to their deviations. Under these conditions the analysis and derivation of closed-form stability functions is even a lot harder, mainly because a high number of cases must be analyzed in parallel. This holds for the investigation of the (*s,nQ*) and (*s,S*) policy. The (*R,S*) policy, in contrast, is easy to analyze because the situation is essentially the same as under *short-term* stability considerations. So, in principle, the *short-term* stability function $\pi(R)$ carries over to the *long-term* treatment under an (*R,S*) rule.

Literature contributions which succeed in transferring the complex mathematical analysis for *short-term* stability to the even more complex *long-term* case are given in Heisig (1998) and Heisig (2002). There, closed-form solutions are presented for the stability functions of the (*s,nQ*) and (*s,S*) policy in the case of *setup-oriented* planning stability. For the investigation of *quantity-oriented* stability, however, no corresponding analysis has been performed so far.

Concerning *setup-oriented* stability, some results from the *short-term* stability analysis carry over to the *long-term* case. This, e.g., holds for the 100% stability property if the lotsize parameters Q and Q_M approach zero or infinity. We also find that with increasing value of Q under an (*s,nQ*) policy the stability metric decreases until it reaches a minimum value in the range of $D \leq Q \leq 2 \cdot D$ and rises monotonously with further increase of Q. For T=1 the minimum level of stability has (by definition) the same value as in the *short-term* case and decreases slightly as the stability horizon T increases. For a large horizon and high demand variability the level of planning stability can go down to only 40%.

When we consider the stability properties of an (*s,S*) rule under *long-term* conditions, numerical investigations reveal some major differences to the *short-term* case. First, the stability function $\pi(Q_M)$ contains multiple points of discontinuity at which the stability level performs considerable jumps. Second, the course of the stability function between these jumps is not monotonous. However, after T jumps things change, and the stability is steadily rising with increasing lotsize parameter Q_M. Third, the point of minimum stability is not necessarily located at a lotsize value of $Q_M=D$ but can also switch to $Q_M=2 \cdot D$ as stability horizon T increases. The level of minimum stability is somewhat lower than for the (*s,nQ*) policy, but different from this policy it can also rise with increasing T. Generally, a global comparison over the whole range of lotsize values reveals that both control policies perform similarly with respect to planning stability.

In Heisig (2002) the formulas for the long-term stability functions are exploited to gain insights into additional aspects. So, the impact of different weighting schemes for the periods of the stability horizon is investigated. Also, the influence of forecast errors, i.e. deviations of the forecasted demand from its expected value, is checked. In Heisig and Fleischmann (2001) and Heisig (2002) it is demonstrated that the steady-state technique for analyzing planning stability can be transferred to an (s,S) control policy which is applied to a product remanufacturing context where additionally stochastic inflows of recoverable products are included.

4.4 Managerial Insights

The analytical stability research reported in this paper provides very useful insights for managing production and materials planning decisions when nervousness in the planning process plays a significant role. Next to cost and service aspects, relevant decision rules as they are given by the basic control policies of (*s,nQ*), (*s,S*), and (*R,S*) type can affect the level of planning stability to a very different extent. This holds for all types of stability measurement (*short/long-term* as well as *setup/quantity-oriented*). Summarizing, from the above research contributions six important managerial insights can be deduced.

1. Planning stability is only affected by the lotsize-specific policy parameter of the respective control rules. This means that the parameter choice concerning service level aspects is not relevant for planning stability considerations.
2. With respect to the stability objective, the periodic (*R,S*) order policy is superior to the two reorder-point policies of (*s,nQ*) and (*s,S*) type. This suggests that the (*R,S*) rule should be preferred as long as other aspects like its missing flexibility and its limited cost effectiveness do not argue against.
3. If *quantity-oriented* stability is relevant within the planning process, the (*s,nQ*) policy is superior to the (*s,S*) rule if *short-term* stability is considered. Since the stability level is constant for each *Q* value, the parameter choice for the (*s,nQ*) policy can be made independent of

planning nervousness aspects in this case. Unfortunately, due to missing research contributions this result cannot be confirmed in the *long-term* stability context.

4. In situations where *setup-oriented* stability is relevant, there does not exist a general superiority of (*s,nQ*) or (*s,S*) rule to the other. Depending on the choice of the lotsize parameters (Q and Q_M), one policy can perform better than the other, but the differences are not serious. In general, the (*s,nQ*) rule with its standard lotsize may be more attractive from a logistical and organizational point of view.
5. When applying an (*s,nQ*) or (*s,S*) policy, from a planning stability point of view the respective lotsize parameter should be chosen carefully. The above analysis reveals that a parameter choice in the range between once and twice the demand forecast value can lead to considerably low stability levels. So, these lotsize values should be avoided unless they are specifically attractive for cost reasons.
6. The level of planning stability highly depends on the variance of the random demand. Concerning the minimum stability level, unfavorable lotsize choice can lead to a stability level below 50% if demand variability is very high. This means that on average order deviations can be so large that more than 50% of worst-case differences can prevail. This holds for both setup and quantity deviations.

5 Challenges for Future Nervousness Research

In this paper, it is demonstrated that useful general insights can be provided by advanced approaches of analytical nervousness research. It would be desirable, however, if some more insights would be generated by extending this research procedure to further problem areas.

The most urgent open question refers to the analysis of the *quantity-oriented* stability of an (*s,nQ*) policy in the *long-term* context. It would be highly interesting if the independence of stability metric π on lotsize Q for *short-term* consideration carries over in this case. If yes, the third managerial insight in section 4 would be valid for all time-oriented instances. Only one single finding from the *short-term* analysis can easily be transferred. Since for $Q \rightarrow 0$ a basic order-up-to-*S* policy is valid in each period, the level of *long-term* stability is identical to the *short-term* level in this case. It is, however, an open question if this level remains constant with increasing *Q* values. Simulation studies of this case in Jensen (1993) and Jensen (1996) do not give a reliable answer to this question. Thus, an analytical study is needed even if it might be extremely cumbersome from a technical point of view.

A completely new research topic would be the analysis of nervousness under non-stationary stochastic demand. From a rough simulation study in Kilic and Tarim (2011) we know that the type of demand pattern has a distinct impact on planning stability under different control policies. For more general and deeper insights an analytical investigation would be needed. This might be feasible for a very simple cyclical demand scheme.

A further challenge consists in extending the analytical approach to a multi-stage production system. Simulation studies like in Jensen (1996) reveal that the *long-term* stability of the control rule at the end-item level has a major influence on the planning stability of the entire system. In this context, a lot-for-lot ordering policy at lower stages seems to be favorable in reducing the total system nervousness. It certainly is worthwhile to investigate analytically if the simulation-based findings can be generalized. At least for a simple linear two-stage system there should be a chance to extend the single-stage analysis.

In literature, there is a major debate on the effectiveness of various nervousness dampening strategies (see Atadeniz and Sridharan (2020)). A widely used approach in this context is the strategy of freezing planned production orders (at end-item level) for a given number of periods. Many simulation-based investigations show that this procedure can lead to a significant reduction of system nervousness. This, however, can come at the expense of a major increase in costs and decline in customer service if the freeze length is too high. An analytical stability study for a single-level system would shed some light into the general interdependence of freezing and planning stability. Such an investigation might be feasible for a relatively simple case of a frozen horizon of one or two periods.

Another approach for nervousness reduction is proposed in the form of using safety stocks for avoiding order deviations. A respective method which can be implemented by extending the reorder-point control policies is described in Jensen (1993). Thereby, nervousness is reduced by abstaining from reorder-point triggered decisions if they deviate from former planned orders and if the inventory level is within a critical range around the reorder point. The width of this range is given

by an additional policy parameter. Simulation results presented in Jensen (1993) could be confirmed and generalized if an analytical study of the stability performance of such a three-parameter policy would be conducted.

The managerial insights formulated in section 4 could be enriched and extended considerably if at least some of these tasks for further research were tackled. The mathematical challenges are enormous. Against the background of potential insights, however, it would be highly desirable if ambitious researchers could be motivated to take on this job without (nervous) hesitation.

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