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On the Economic Value of Supply Chain Visibility: The Example of Improved Emergency Ordering

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ON THE ECONOMIC VALUE OF SUPPLY CHAIN VISIBILITY: THE EXAMPLE OF IMPROVED EMERGENCY ORDERING

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Abstract

Location technologies such as GPS or GSM cell tracking can be used to improve the control of production and transport processes along the entire supply chain. In this paper, we particularly consider the benefits of location systems with regard to supply chain visibility for improving emergency ordering decisions. For this purpose, we first present an overview of the underlying base technologies that can be used for supply chain monitoring today and a review of prior research on inventory control with emergency ordering. With the help of a simulation model, we show that higher supply chain visibility can be used to identify and avoid unnecessary emergency orders, resulting in cost savings for the overall inventory system. In addition, we identify optimal levels of supply chain granularity and discuss why the maximum resolution that may be achievable from a technological perspective does not necessarily lead to cost-optimal results.

Keywords: Location Systems, Object Tracking, Emergency Ordering, Inventory Control

1 INTRODUCTION

In recent years, an increasing number of white papers, market analyses, articles in trade magazines, conference proceedings and academic journals have discussed the benefits of novel ubiquitous computing technologies with regard to supply chain visibility. With the advent of wireless sensors, Radio Frequency Identification (RFID), location systems, etc. information systems get the capability of collecting data from the physical world in real-time at a fraction of the cost of traditional manual data entry. As a consequence, companies get not only more information but also more fine-grained information on the state of physical goods, unplanned exceptions in the execution of logistical processes, the performance of their suppliers and logistics service providers, and so on. The purpose of achieving visibility is primarily for improving an organisation's own internal decision making and operating performance, but also for better coordinating processes between partners along the entire supply chain.

This paper concerns itself particularly with the use of location systems in inventory management. We consider the case of a distributor who has to fulfil its customers' demand by ordering from a remote supplier with stochastic lead times. In order to avoid stock-outs, the distributor has the option to trigger emergency orders at higher cost if a regular order arrives late. Real-world examples of such scenarios can, for example, be found in the automotive industry with suppliers of critical parts that have moved to Eastern Europe while their customers are still operating their production lines in Western Europe. The risks of long geographical distances between suppliers and OEMs in today's Just-In-Time supply chains have motivated some OEMs to deploy tracking systems based on GPS, RFID, and similar technologies. Against this background, the aim of this contribution is to investigate to what extent location information can improve a company's inventory control process and which impact different levels of information granularity may have on the performance of ordering decisions.

The remainder of this paper is organised as follows. In section 2, we give a short summary of state-of-the-art location technologies. Section 3 provides a review of related work on inventory control with emergency ordering. The next section comprises a simulation study of emergency ordering under different location visibility levels. The paper closes with a summary and conclusions.

2 TECHNOLOGY BACKGROUND

Location systems are usually associated with the Global Positioning System (GPS), a satellite-based system which was developed by the end of the 1980s. GPS uses lateration of at least four satellite signals and achieves a tracking accuracy of about 15 m; higher accuracies are possible using "Differential GPS (DGPS)" but require more than one receiver. The major drawback of GPS is in the fact that satellite signals are too weak to penetrate walls, i.e. (Borriello et al. 2005).

A second popular procedure to generate location information is to use cell information from the mobile network, e.g. GSM. The typical size of GSM cells can vary between 2 km and 20 km. However, additional accuracy can be achieved with the use of sector information that limits the position of an object to only one area that is covered by the GSM cell. Though the overall location accuracy is much worse than GPS, GSM cell information allows for object tracking even in buildings (Varshavsky et al. 2007).

An alternative to GPS and GSM is the use of Wi-Fi hotspots in metropolitan areas. The underlying principle is about the same as GPS but relies on signal strength information from WLAN access points. As LaMarca et al. (2005) demonstrate, the accuracy of Wi-Fi tracking can surpass GPS. A comparison of the three before-mentioned technologies and others is given in Figure 1.

It should be noted that in recent years, a number of indoor location systems have evolved in parallel that use infrared, ultrasound or radio frequency technology to locate people or objects in buildings.

Furthermore, RFID – though being supposed to serve as an automatic identification technology – can also be used for location purposes. Firstly, RFID signal measurements can be processed in the same way as Wi-Fi signals and provide information on the distance between the RFID tag and a reader device. Secondly, RFID readings can be interpreted as distinct location data if the tag is associated to the known position of a reader.

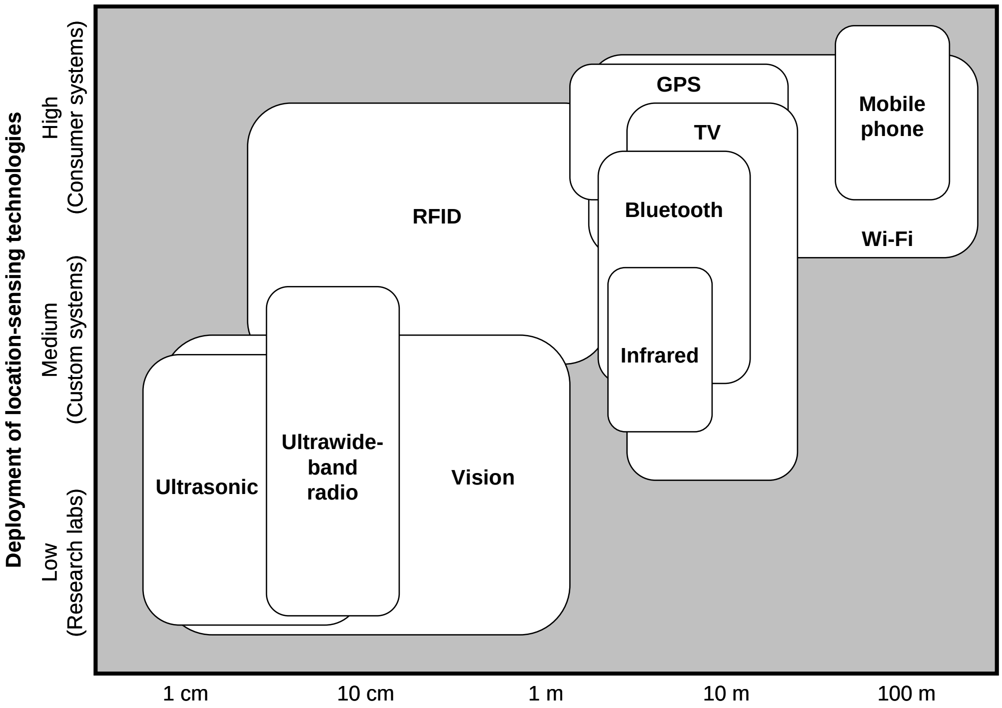

Figure 1. Location-sensing technologies (adapted from Hazas et al. 2004)

3 RELATED WORK

Research work related to the subject of in this paper stems primarily from operations management literature on (*R*, *Q*) inventory policies, stochastic replenishment lead times, emergency ordering, and multi-echelon supply chains. The following literature review is therefore organised accordingly.

Early research on inventory control systems includes the work by Hadley and Whitin (1963). The authors introduce (*R*, *Q*) policies for continuous inventory control and show optimal inventory control policies in the case of stochastic replenishment lead times. In a more recent work, Silver, Pyke and Peterson (1998) describe the basic concept of this inventory management policy while deriving a plethora of decision rules for different settings where safety factors or specific stock out costs are known. They assume replenishment lead times to be deterministic and unsatisfied demand to be backlogged until the replenishment order arrives. The order quantity *Q* is not to be determined in their study and is rather treated as an exogenous variable. Unlike this last assumption, Federgruen and Zheng (1992) propose an algorithm to determine reorder point *R* and order quantity *Q* simultaneously.

Inventory management under variable replenishment lead times has also been discussed in the contribution by Hadley and Whitin (1963). They show that stochastic lead times might result in order crossing, though the probability of crossover becomes negligible once the reorder intervals become large compared to the replenishment lead times. An alternative approach to prevent order crossing is taken by Liberatore (1979), who assumes that unit demands are non-interchangeable. Under the same assumption, Sphicas (1982) identifies bounds for the decision variables of the replenishment process in variable lead time while the demand per time unit is kept constant. Consideration to other special cases of stochastic replenishment lead times is given by both Kaplan (1970) and Zipkin (1986).

Emergency ordering refers to an inventory system with two supply modes. Supply is usually ordered from one distribution channel while the other is used if a standard order is late and is therefore likely not to arrive in time. The 2^{nd} distribution channel is typically characterized by shorter replenishment lead time but higher acquisition costs as in the work by Moinzadeh and Nahmias (1988). In earlier research, Rosenshine and Obee (1976) discuss emergency orders in a standing order inventory system. Additional costs for both emergency ordering and overstocking are considered in their work, but the restocking process is limited to fixed replenishment lead times. Allowing variable, gamma-distributed lead times, Johansen and Thorstenson (1993) show optimal and approximate (r, Q) policies for inventory management with lost sales. In a more recent work, Tagaras and Vlachos (2001) develop an approximate model to decide upon both the necessity and the size of an emergency replenishment in a setting with deterministic lead times. Their findings are based on a base stock periodic review policy and are especially applicable in settings with high shortage costs and infrequent, though expensive emergency ordering costs. The replenishment model is restricted to only one emergency order per review cycle to restrain computational efforts. This limitation is relaxed in the work by Teunter and Vlachos (2001), who allow more than one emergency shipment per review period.

Multi-echelon inventory problems have been considered early in a work by Clark and Scarf (1960). They show optimal reorder policies for a base stock periodic review inventory system with both linear purchasing and shipping costs and backlogged demand. The authors discuss both linear and diverging, tree-type supply chain structures and provide a proof of optimality of the suggested inventory management policy for the former case in the absence of setup costs. Chen and Zheng (1994) discuss a more general approach by allowing setup expenditures, though optimal inventory control then is no longer possible. The authors develop lower bounds for the management of multi-echelon inventory systems instead. In a recent work, Moinzadeh (2002) describes the impact of information exchange in a multi-echelon supply chain structure for a single product. In the author's setting, the supplier has access to information on both the retailer’s inventory position and the current demand at the retail level and uses this information for its own replenishment orders. The supply chain follows a diverging structure with several retailers, which all receive their replenishments directly from one central supplier. A linear multi-echelon supply chain with several consecutive nodes, however, is not considered in that research.

4 SIMULATION STUDY

4.1 Model development

In the following, we investigate to what extent emergency ordering can be improved if an organisation is aware of the position of regular orders in the supply chain. For this purpose, we adopt the concept of using order progress information in an emergency order setting as developed by Gaukler and Hausman (2008). Our work draws an important distinction, however: While the number of order stages remains a constant in their study, our numerical experiments treat supply chain granularity as a variable, allowing for the comparison of different levels of supply chain visibility. In this context, we consider a simulation model with a distributor who continuously satisfies customer demand and uses both regular and emergency ordering for replenishment. By default, the distributor sources from an inexpensive, though remote supplier with long and stochastic replenishment lead times. In case the distributor is about to stock out, it can also order from a local, but costly supplier with a short deterministic lead time. The demand at the distribution centre is created by customers whose inter-arrival times follow an exponential distribution with parameter λ. In order to avoid the undershoot problem as discussed by Hill (1988), each customer is presumed to request only one stock keeping unit from the distributor. An illustration of this supply chain structure is given in Figure 2.

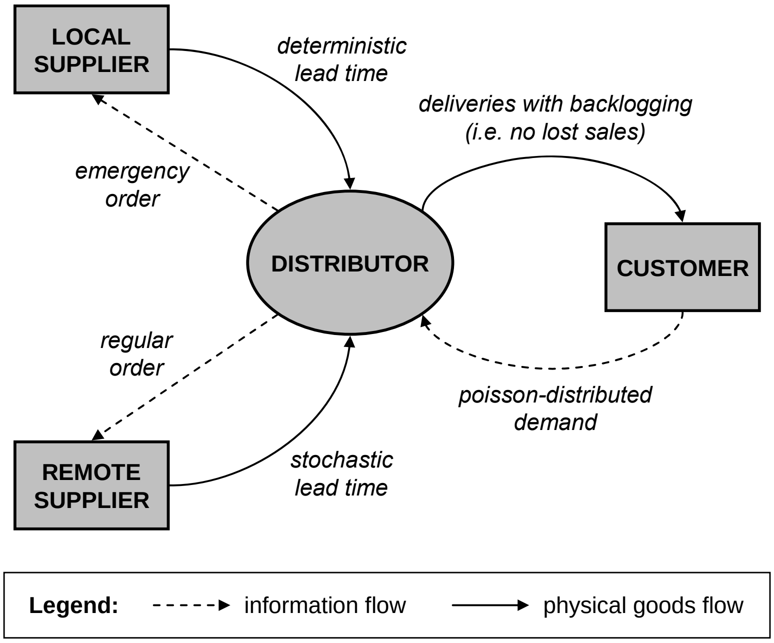

Figure 2. Structure of the simulation model

The regular replenishment process follows a conventional (*R*, *Q*) policy. Each time the inventory level drops to a pre-defined reorder level *R*, a standard replenishment of fixed quantity *Q* is ordered from the distant supplier. While waiting for the arrival of the replenishment, the inventory continues to satisfy customer demand from the remaining on-hand inventory. If the demand until order arrival exceeds the on-hand inventory available at the beginning of the stochastic replenishment cycle, a stock-out situation occurs. Unsatisfied demand will then be backlogged and met later on arrival of the regular shipment.

In order to avoid these out-of-stock situations, the distributor has the option to release emergency orders. Therefore, a reorder threshold for emergency orders R^E is introduced as suggested by Tagaras and Vlachos (2001). Thereby, an emergency order point $R^E < R$ guarantees that the distributor always sources from its regular supplier first. Once the inventory level hits this second threshold, an emergency replenishment of size Q^E is requested from the local supplier that will arrive after the deterministic lead time $l^E > 0$.

Though enhancing the standard (*R*, *Q*) policy by an emergency order option can bring significant cost improvements, some drawbacks remain, as the work by Gaukler and Hausman (2008) shows: Owing to the stochastic replenishment lead times of the regular orders, some emergency orders tend to arrive after their regular counterparts, rendering them useless for preventing out-of-stock situations. From an ex post perspective, they are dispensable and could have been avoided. The problem is that the conventional emergency ordering process does not consider how far the standard order has already proceeded on its way to the distributor. Even if a regular order is close to arrival, the emergency order is released if the inventory level hits the corresponding reorder point.

In this setting, the use of location technologies allows for tracking the standard shipment on its way through the supply chain and makes emergency ordering decisions based on this information possible. The additional visibility, which the location technology provides, is reflected in the model context by splitting up the regular shipping distance into several consecutive supply chain segments. Herein, the assumed tracking technology determines the corresponding level of supply chain visibility.

In the following numerical study, we want to show how increased supply chain visibility can improve traditional emergency ordering concepts. Starting off from the base cases of a traditional (R, Q) policy and an (R, Q) policy with emergency orders, we discuss which additional benefit a single monitor in the supply chain can bring and were it is best to be located for achieving cost-optimal results. We then show how increasing supply chain visibility can lower total system costs even further. Table 1 lists the relevant model parameters that are used in our model.

c^{IV}	Inventory holding cost per unit per day
c^{BL}	Backlogging cost per unit per day
c^{OD}	Fixed ordering cost
c^{EO}	Fixed emergency ordering cost
l	Mean lead time for regular orders
l^{EO}	Lead time for emergency orders
M	Number of transit monitors in the supply chain
λ	Average daily customer demand
Q	Regular order quantity
R	Regular reorder point
Q^{EO}	Emergency order quantity
R^{EO}	Emergency reorder point
T	Time horizon per replication
TC	Objective function (i.e. total cost)

Table. 1. Reference list of model parameters

4.2 Numerical Evaluation

For all simulation runs described in this subsection, we assume that the travel time from the supplier to the distributor comprises 32 exponential sojourn times of the standard order, i.e. the total replenishment lead time is Erlang with l = 2.5 days. The customer arrival process also follows an exponential distribution with the average number of customers arriving per day being λ = 10. Assumed cost factors for inventory carriage, backlogging, ordering, and emergency ordering are specified as:

- c^{IV} = 10 €
- c^{BL} = 500 €
- c^{OD} = 100 €
- c^{ED} = 200 €

All simulations runs cover a time horizon of T = 3650 days and we conducted 100 replications for each parameter constellation. The simulation models were programmed and performed with Visual Basic in Microsoft Excel, where the generated output data was also analysed and further processed. Alternating random number generators were used to avoid any computational bias in the simulation study.

4.2.1 Traditional (R, Q) policy

In a first step, the optimal solution of a traditional (R, Q) policy is identified. For the base parameters specified above, the objective function yields a cost minimizing solution of TC = 1128488.12 € with Q = 34 and R = 33. The average inventory level of this solution is 24.1 SKUs, the average backlog level is 0.08 SKUs, and the average number of standard orders in the time horizon aggregates to 1073.98. The identified solution being the global cost minimum is guaranteed by the convexity of the objective function (cf. Figure 3).

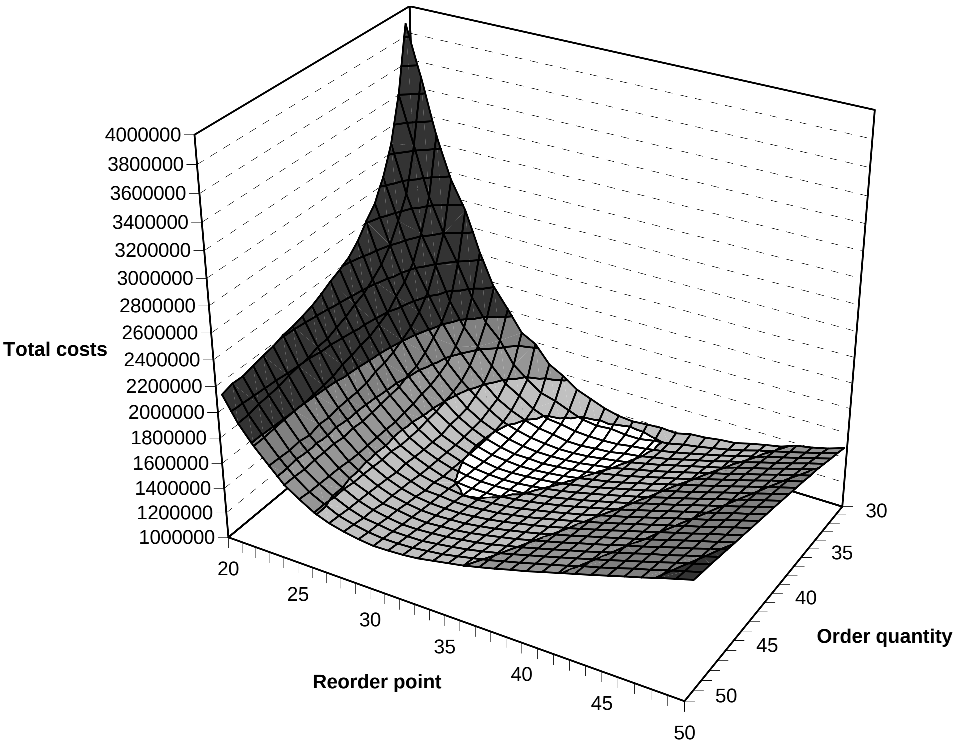

Figure 3. Objective function under the (R,Q) policy

4.2.2 (R, Q) policy with emergency ordering

In a second step, the (R, Q) policy is now enhanced by allowing emergency ordering from the local supplier. Once the inventory level at the distributor hits R^{EO}, an emergency order is issued that arrives after a deterministic emergency replenishment lead time of l^{EO} = 1 day. Costs are minimized by the parameter constellation Q = 23, R = 33, Q^{EO} = 10 and R^{EO} = 5, while Q^{EO} = 10 was treated as an exogenous variable. The total costs add up to 1059457.45 € which translates to an improvement of 6.12% in total when compared to the conventional policy without emergency orders. This solution adds up from an average inventory level of 19.36 SKUs, an average backlog of 0.06 SKUs, and a total of 1362.32 standard and 517.51 emergency orders. These results show that emergency orders now partially replace parts of the SKUs that were provided by the regular replenishment mode in the first run. The cost savings are therefore mainly achieved by reductions in inventory carrying and backlogging costs, though these are partially compensated by the increased ordering costs.

4.2.3 Emergency ordering with transit monitors

The emergency ordering process is now enhanced by a single transit monitor, i.e. a device that informs the distributor about orders moving from one part of the supply chain to the other. The transit monitor divides the supply chain into two independent segments for which individual emergency order thresholds can be set. Figure 4 illustrates this concept.

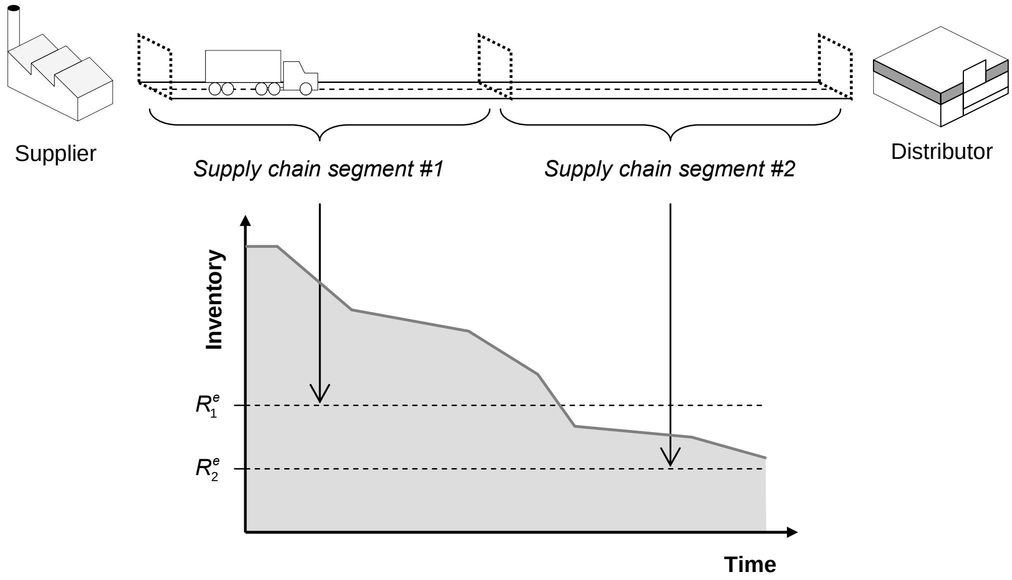

Figure 4. Emergency ordering with transit monitors

Our aim is to find a) the optimal thresholds R_1^{EO} and R_2^{EO} for the two segments and b) the optimal position of the transit monitor. With $Q = 23$ and $R = 33$ being adopted from the previous simulation step, we determine the cost-minimizing values by simulating each possible combination of the three parameters. Figure 5 depicts the minimal costs for each transit position ("31" denotes the first transit after the order was shipped; "1" denotes the last transit before the order arrives at the distributor). As can be seen, the transit monitor is best to be placed in the middle between distributor and standard supplier.

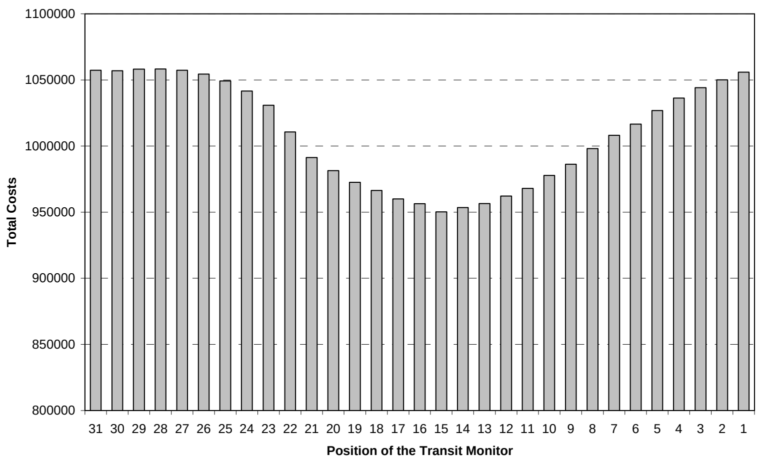

Figure 5. Cost reduction by transit monitoring at different positions in the supply chain

At $R_1^{EO} = 13$, $R_2^{EO} = -5$, and a transit monitor position equalling 15, the total costs are 950101.37 €. This solution incorporates an average inventory level of 17.56 SKUs, average backlogs of 0.04 SKUs, 1388.22 standard orders, and 454.66 emergency orders. This result and the corresponding graph in Figure 5 can be explained as follows: If the transit monitor is positioned close to the supplier, its value is limited as the location uncertainty of the shipment is still now. If the monitor is positioned close to the distribution centre, however, its use is also limited as emergency orders might then be issued too late and cannot hedge against an imminent out-of-stock situation any more. These diametric effects endorse a transit monitor position in the middle of the supply chain.

I should be noted that, from a practitioner's perspective, the deployment of a single transit monitor in reality might be constrained for technical and geographical reasons. The determined optimal monitoring location might be in a remote rural area lacking mandatory technical infrastructure access, necessitating its relocation at the disadvantage of inferior supply chain performance.

4.2.4 The impact of increasing supply chain visibility

In a fourth and last step, we investigate the influence of an increasing supply chain granularity. While the simulation done in the previous section discussed the benefit of positioning a single transit monitor in the supply chain, the number of transit monitors is now increased and the supply chain is divided up into 2, 4, 8, 16, and 32 equal sections (cf. Figure 6).

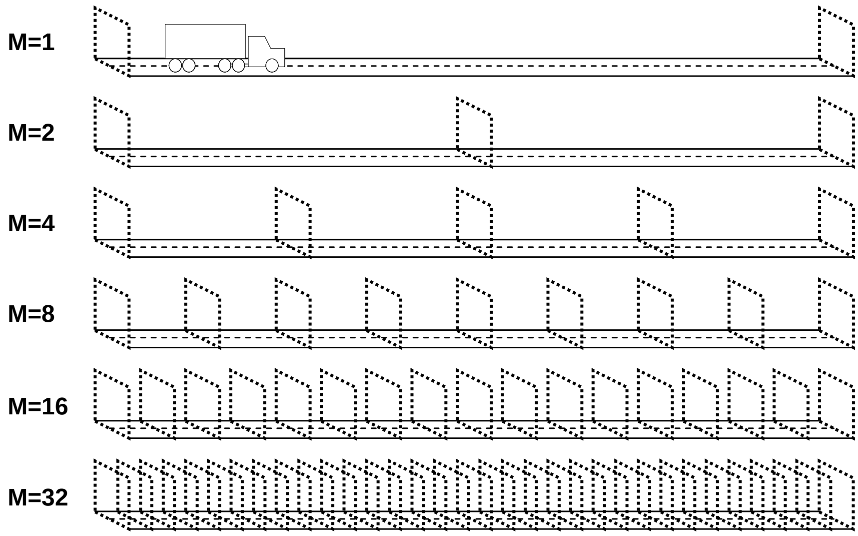

Figure 6. Supply chain segmentation with increasing resolution

The emergency order thresholds of the corresponding sections are computed by an iterative search algorithm: Beginning at $M = 2$, the starting values for the two emergency order points are the optimal R^{EO} from $M = 1$, which equals the cost minimizing solution for R^{EO} from section 4.2.3. Now, the emergency order threshold for the first section is tested for different values and the cost minimizing value is kept. Then, the heuristic continues with seeking the optimal value for the second section. Once the two new emergency order thresholds are found, the heuristic proceeds to the next level of supply chain granularity $M = 4$. Here, the first two sections use the optimal value from the first supply chain step of $M = 2$, the second two sections the optimal value from the second supply chain step. Again, the emergency order thresholds are set iteratively and the solutions serve as input for the thresholds of the next visibility level. As the objective function is convex, one iterative run through all emergency order thresholds is sufficient to yield an optimal solution for each level of location granularity. The optimality of the identified solutions has also been cross-checked for $M = 2$ and 4 by testing all possible combinations of emergency order thresholds. Their optimal values at different visibility levels are shown in Figure 7.

The total costs that emerge from these optimal emergency order points at different levels of supply chain granularity are shown in Table 2. In general, an increasing order progress visibility tends to lower the total costs of the inventory system. Emergency order decisions can be made on more precise information, thereby helping to avoid unnecessary emergency replenishments and triggering them only when the distributor is really about to stock out. However, the total cost improvements become smaller

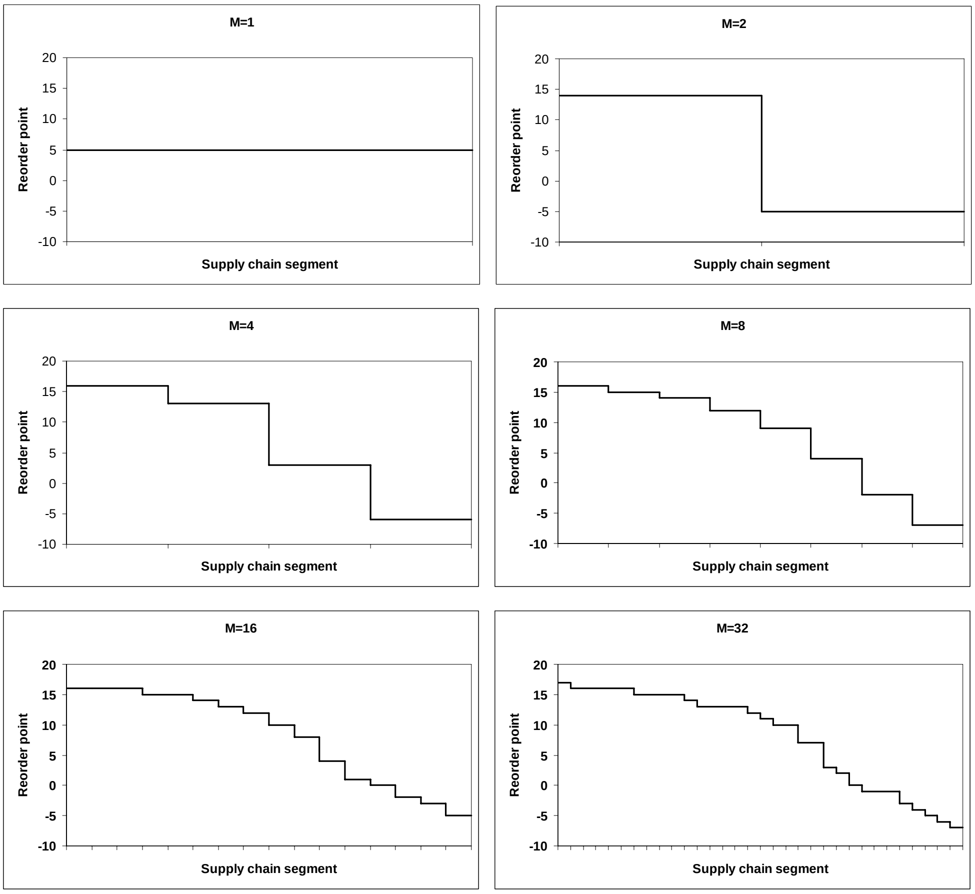

Figure 7. Optimal reorder points under different visibility levels

M	Performance indicators				Total costs			
	Inventory	Backlog	Orders	E.Orders	Mean	SD	CI	Δ
1	19.36	0.06	1362.45	522.40	1068568.79	13618.37	±2669.15	-5.31 %
2	17.71	0.04	1384.50	468.62	957031.72	10850.27	±2126.61	-15.19 %
4	17.26	0.05	1393.45	443.55	952755.41	10699.40	±2097.04	-15.57 %
8	17.44	0.04	1393.93	441.14	944104.42	9320.91	±1826.86	-16.34 %
16	17.38	0.04	1393.75	441.61	942566.43	10552.24	±2068.20	-16.48 %
32	17.60	0.04	1391.85	451.76	941526.75	8338.96	±1634.40	-16.57 %

Table 2. Simulation results under different visibility levels
(SD = Standard deviation, CI = Confidence interval at 95% confidence level,
Δ = Relative cost reduction compared to the traditional (R,Q) policy)

and smaller the more the supply chain visibility increases. For M > 8, no significant improvements can be made any more as the overlapping confidence intervals for M = 8, 16, and 32 show. The reorder points in Figure 7 also hint at another finding: The applied level of supply chain visibility is not of equal importance throughout the replenishment process. While segments close to the supplier have only a low importance for triggering emergency orders, this importance increases towards the end of the standard replenishment cycle, when the standard order has almost arrived at the distributor and it is most likely to run out-of-stock. It is evident that, similar to the limitations discussed in 4.2.3, this fourth concept is constrained by the real world constraint with regard to the deployment of transit monitors. As the number of supply chain segments is even higher as in the previous scenario, it is now even more likely that single monitors would have to be relocated.

5 CONCLUSIONS

This paper has shown the value of using location information to increase supply chain visibility for improved emergency order processes. On the one hand, our simulation study confirmed the main findings by Gaukler and Hausman (2008) regarding the overall value of location information to emergency ordering. On the other hand, we have shown that the position of reader devices and the granularity of the entire object tracking system have a significant influence on its economical value. Our results indicate that, while the efficiency gain was already considerably high for rather coarse granularity, further increases in visibility yielded no significant cost savings any more. As high levels of resolution can usually only be achieved by extremely high investments in technical infrastructure, the optimal resolution for supply chain applications is not necessarily the maximum resolution that can be achieved technically today. Therefore, the appropriate technology (i.e. the optimal level of supply chain visibility M^*) has to be selected in accordance to the cost considerations that are depicted in Figure 8.

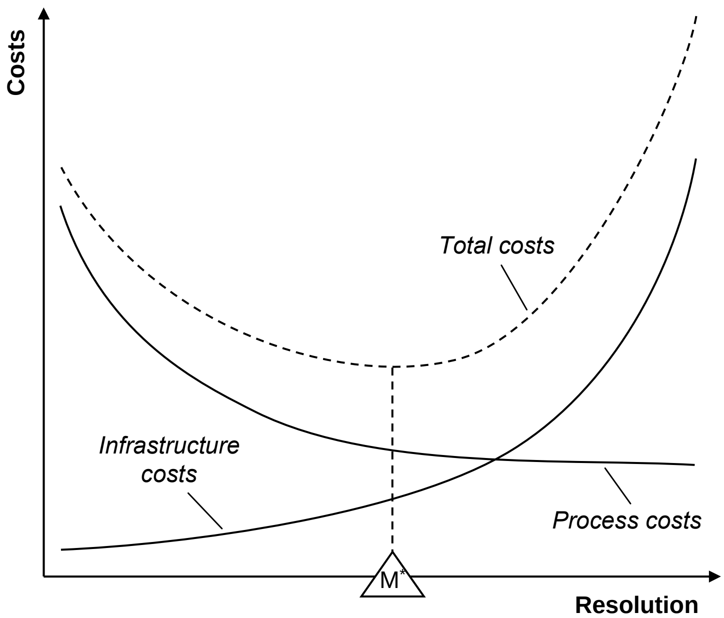

Figure 8. Trade-off between process cost reduction and increasing infrastructure costs

However, it should be noted that our research also comes along with some limitations that need to be considered when interpreting our findings. Though the basic concept of improving supply chain performance by order progress information is evident, the exemplary nature of this numerical study usually prohibits a one-to-one adaptation in real world scenarios. Suggestions for further research therefore include a detailed sensitivity analysis that takes different underlying cost factors into account, albeit the general influence of changing cost parameters may also be derived intuitively from the structure of our simulation model. In addition, next research steps could also include the analytical modelling of the shown process of emergency ordering at different levels of supply chain visibility. Further consideration might also be given to the use of location technology in other domains of production and supply chain management.

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