Business Models for Condition Based Maintenance Services

Quan Zhu (corresponding author) and Henk Akkermans

Tilburg University
Warandelaan 2, 5037AB, Tilburg, the Netherlands
Tel: +31 13 466 3334
Email: qzhu@uvt.nl

Abstract
Commonly, maintenance is performed on a corrective basis. When the equipment condition can be monitored, a condition based maintenance (CBM) strategy can be implemented by the original equipment manufacturer (OEM). CBM has the potential to help boost business for both the OEM and its customers, but when applying CBM practices, managers always face the problem of transparency from business context. This is due to organizational complexity and dynamic complexity: within both the OEM and its customers, the perspectives and interests of maintenance, service, sales, finance, and others differ, and need to be reconciled; all these interrelations evolve over time, so any static picture is bound to be increasingly more incorrect as time passes. Through system dynamics modeling of a real case, we clearly show the performance improvements for both the OEM and its customers from the scenario with rare CBM practices to the scenario with CBM as a majority. Managers from different departments can understand the dynamic behavior of CBM through their interactions (i.e. organizational complexity) and the lead time involved (i.e. dynamic complexity). Moreover, via sensitivity analysis, we provide further suggestions to better implement CBM in practice.

Introduction
Due to today's dynamic and competitive environment, more and more manufacturers turn to lean manufacturing to be highly responsive to customer demand by reducing waste. Like other lean practices, outsourcing equipment maintenance to improve the performance has become a key aspect in the production process (Bhamu & Sangwan, 2014). Meanwhile, the original equipment manufacturer (OEM) would like to provide such maintenance service to extend its business scope. Commonly, maintenance is performed on a corrective basis. When the equipment condition can be monitored, a condition based maintenance (CBM) strategy can be implemented, according to which the decision of maintenance is taken dynamically on the basis of the observed condition of the equipment. The advantage of this policy lies in the possibility of preventively maintaining the equipment only when necessary, thus, in principle, saving resources and equipment availability (Marseguerra, Zio, & Podofillini, 2002). Taking such benefits as given, previous literature mainly focused on condition monitoring techniques. However, when applying CBM practices, managers always face the problem of transparency from business context: businesses remain reluctant to share data (Akkermans, Bogerd, & van Doremalen, 2004). There are many internal and external stakeholders: within the OEM, the perspectives and interests of maintenance, service, sales, finance, and others differ, and need to be reconciled. Within its customers, again different perspectives and interests exist and need to be reconciled. All these interrelations evolve over time, so any static picture is bound to be increasingly more incorrect as time passes. Therefore, besides technical complexity driven by different condition monitoring techniques, organizational complexity and dynamic complexity are at least equally important. By considering both

organizational complexity and dynamic complexity, we will create a decision support tool to help discover business opportunities for both the OEM and its customers.

In this paper, we will investigate the dynamic behavior of CBM via a case study. In the case, our client (the OEM) can offer extensive condition monitoring facilities in its new generation of machines. The managers of the OEM would like to elaborate the dynamic behavior for both the OEM and its customers to boost business via CBM practices, so that an agreement on promoting CBM can be reached within the OEM and a promotion plan to sell CBM service to its customers can be formed. Through system dynamics modeling, we will clearly show the performance improvements for both the OEM and its customers from the scenario with rare CBM practices to the scenario with CBM as a majority. Moreover, via sensitivity analysis, we will test the robustness of our scenario analysis results and provide further suggestions to better implement CBM in practice.

The structure of this paper is organized as follows: section 2 presents a literature review on CBM and organizational complexity and dynamic complexity in practice. This is followed by our model illustration and scenario analysis results in section 3. Furthermore, the sensitivity analysis results are shown in section 4. The paper is concluded with suggestions to better implement CBM in section 5.

Literature Review

From corrective maintenance to CBM

In the past, corrective maintenance accounted for most maintenance practices (Jonsson, 2000), which is also applied in our case. In terms of corrective maintenance, actions for maintaining equipment are not undertaken before a machine breakdown occurs. Such a corrective fire-fighting strategy leads to many unexpected machine breakdowns with the consequence of decreasing equipment availability. In a dynamic and competitive environment, corrective maintenance must be regarded as anachronistic, because the overall performance will suffer in terms of cost, quality, time, and flexibility (Thun, 2006).

As it became too expensive to run the equipment until breakdown, various preventive policies were developed (Jonsson, 2000). For example in our case, to improve the efficiency of every visit to the customer, the technicians of the OEM would combine corrective maintenance with some opportunity based preventive maintenance. However, the performance of such preventive maintenance heavily depends on the technicians' own knowledge and experience, as well as on-site situations. Therefore, it is highly possible that the little maintenance jobs may be done rather than the big ones, which are repeatedly delayed (Jonsson, 2000).

In contrast, CBM concerns preventive maintenance initiated as a result of knowledge of the changed condition of any particular item from routine or continuous monitoring (Jonsson, 2000). The motivation of CBM is that 99% of equipment failures are preceded by certain signs, conditions, or indications that a failure is going to occur (Ahmad & Kamaruddin, 2012). CBM attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is evidence of abnormal behaviors of a physical asset. It is a proactive process, which requires the development of a predictive model that can trigger alarm for corresponding maintenance (Peng, Dong, & Zuo, 2010). In our case, such model is embedded in the condition monitoring facilities in OEM's new generation of machines. Condition based information can be collected through such facilities, so that a maintenance plan can be proposed to the customers before a breakdown happens. CBM can be arranged on less busy days. Its performance is more predictable and better than that of corrective maintenance.

Organizational complexity and dynamic complexity in practice
CBM is accompanied by a more complex maintenance system, because many different facets of maintenance interact with each other. First, there is a problem that the "logic" of corrective maintenance might still mitigate the positive effect of CBM. Owing to machine breakdowns, the maintenance department used to be busy with repairing machines. Accordingly, the maintenance department devoted less time on maintenance tasks on a regular basis (Thun, 2006). The engineers need to get used to more maintenance tasks than repair ones, when CBM is applied. They need time to change, both physically and mentally.

Second, CBM can make maintenance practices into company-wide issues, i.e. some activities should also be performed by other departments than the maintenance department to get the most benefits from CBM practices (Jonsson, 2000). For example, the sales department and the service department expect to sell more machines and service products, respectively, after implementing CBM. Their logic rests on the improvement of reputation: CBM practices help improve the productivity of machines, which improves the reputation of the OEM and finally economic outcomes. However, in practice, the story is different. According to Rindova, Williamson, Petkova, & Sever (2005), reputation consists of two dimensions: (1) customers' perceptions of the OEM as able to provide quality goods/service (i.e. "being good") and (2) the OEM's prominence in the minds of customers (i.e. "being known"). Their research results suggest that only prominence contributes significantly to the price premium associated with having a favorable reputation. Positive evaluations of quality increase prominence and, therefore, may serve as inputs in the collective processes through which prominence develops. Simply speaking, "being good" is just a start; only after "being known" can the OEM achieve more economic outcomes. Thus, speeding up such cognitive processes may significantly influence the gains of CBM practices.

The same logic applies to different departments in the OEM's customers. With the implementation of CBM, their operations department should facilitate continuous improvement and learning to incorporate the CBM output (i.e. increased productivity of machines) to develop and exploit better practices in supply chains (Hyland, Soosay, & Sloan, 2003). Meanwhile, their sales department will face the same challenge that it takes time to turn from "being good" to "being known" and finally to gain premium.

In summary, different departments in the OEM as well as its customers have diverse expectations from CBM practices and need to perform dissimilar activities to guarantee the success. Their interactions will evolve over time and their payback periods vary from each other. Only when their perspectives and interests are reconciled over time can CBM be successfully implemented.

Model Illustration and Scenario Analysis
We will report two simplified models: one is for the OEM, and the other is for an OEM's customer. All the inputs (including data and perception of trends) were provided by our client (the OEM). The detailed models and input settings can be found in our supplement documents. Our scenario

analysis will report the performance change from the scenario with rare CBM practices (in the model, we set the "CBM percentage" as 10%) to the scenario with CBM as a majority (in the model, we set the "CBM percentage" as 90%). The simulation ran for 200 weeks (about 4 years) to better represent the real situation.

Model for the OEM

Five departments (i.e. sales, R&D, maintenance, service, and finance) are interacted in the model for the OEM (Figure 1). "Cumulated Margin" is determined by the speed of both "Revenue" increase and "Cost" consumption. Briefly speaking, there are two sources for "Revenue" increase and three sources for "Cost" consumption. "Revenue" is generated by selling machines ("Sales revenue") and service/consumables ("Service charge"). While "Cost" is formed by making/installing machines ("Machine making cost"), maintenance ("Maintenance cost"), and sales staff/training consumption ("Sales cost").

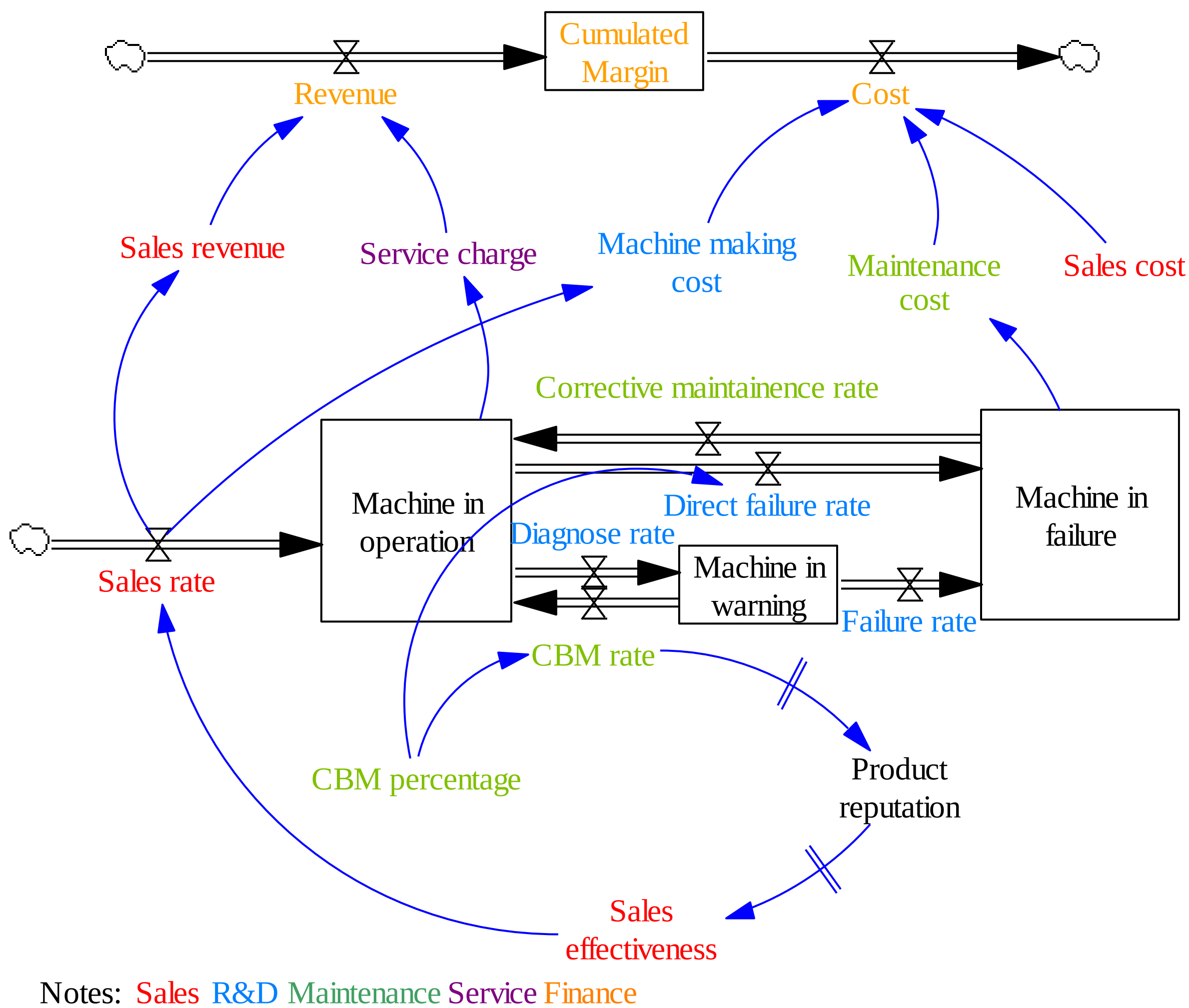

Figure 1. Model illustration (the OEM)

"Sales revenue" can be improved by the increase of "CBM percentage" through the improvement of "Product reputation" (i.e. positive evaluations of quality) and "Sales effectiveness" (i.e.

prominence), with a rather long lead time (two delays shown in Figure 1). Due to the long relationship distance (both the number of variables involved and the long lead time), the impact of “CBM percentage” increase on “Sales revenue” is weak. According to our scenario analysis result (Figure 2), the performance difference becomes obvious around Week 135. Although in percentage, the final improvement of “Sales revenue” in Week 200 is only 1.6%, the increased amount is considerable, which is 186,700 euro/week.

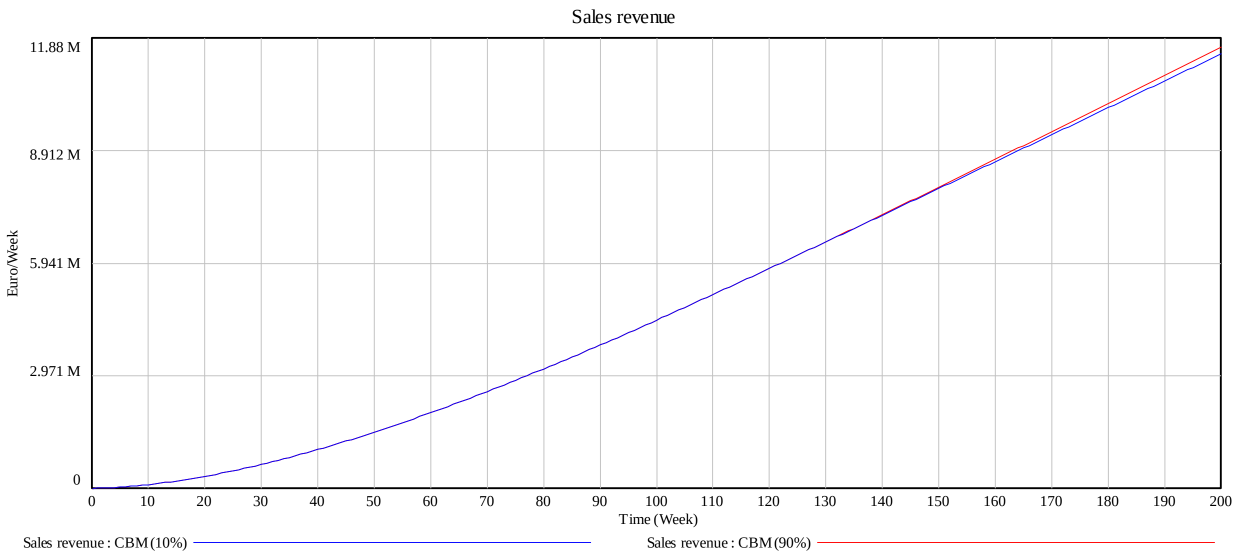

Figure 2. Scenario analysis result for “Sales revenue” (the OEM)

“Service charge” is directly related to the number of “Machine in operation”, which can be improved by increasing “CBM rate” (through “CBM percentage” increase) in a short run and by increasing “Sales rate” (through “CBM percentage” increase with a long lead time, similar to the improvement of “Sales revenue”) in a long run. Figure 3 shows our scenario analysis result for the OEM’s “Service charge”. Both in percentage (9.6%) and in amount (656,990 euro/week), the improvement is significant.

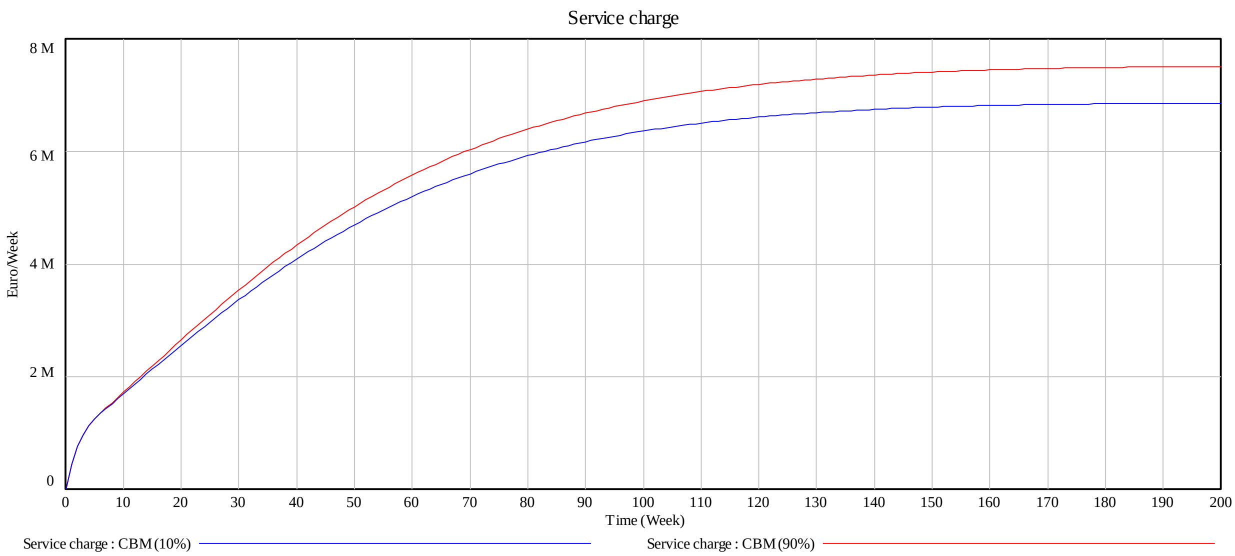

Figure 3. Scenario analysis result for “Service charge” (the OEM)

Similar to the increase of “Sales revenue”, “Machine making cost” will also be increased, since new machines will be made. But as there is always a margin between the sales price of the machine and the making cost of the machine, such increase will not hurt the “Cumulated margin”. The trend of the increase of “Machine making cost” is demonstrated in Figure 4. The increase becomes obvious around Week 125. In the end (Week 200), “Machine making cost” increases 42,212 euro/week (4.6%).

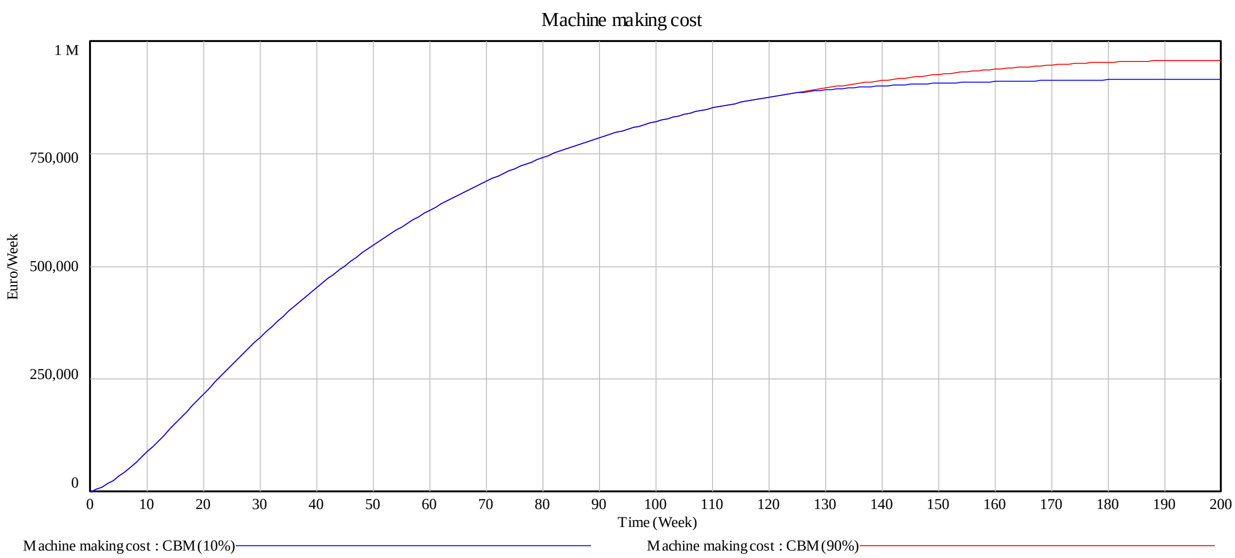

Figure 4. Scenario analysis result for “Machine making cost” (the OEM)

“Maintenance cost” is directly related to the number of “Machine in failure”, which is lowered by the increase of “CBM percentage” via “Direct failure rate”. Due to the short relationship distance, “Maintenance cost” is decreased expressively in our scenario analysis result (Figure 5). In Week 200, the amount is declined by 71.5% (991,348 euro/week).

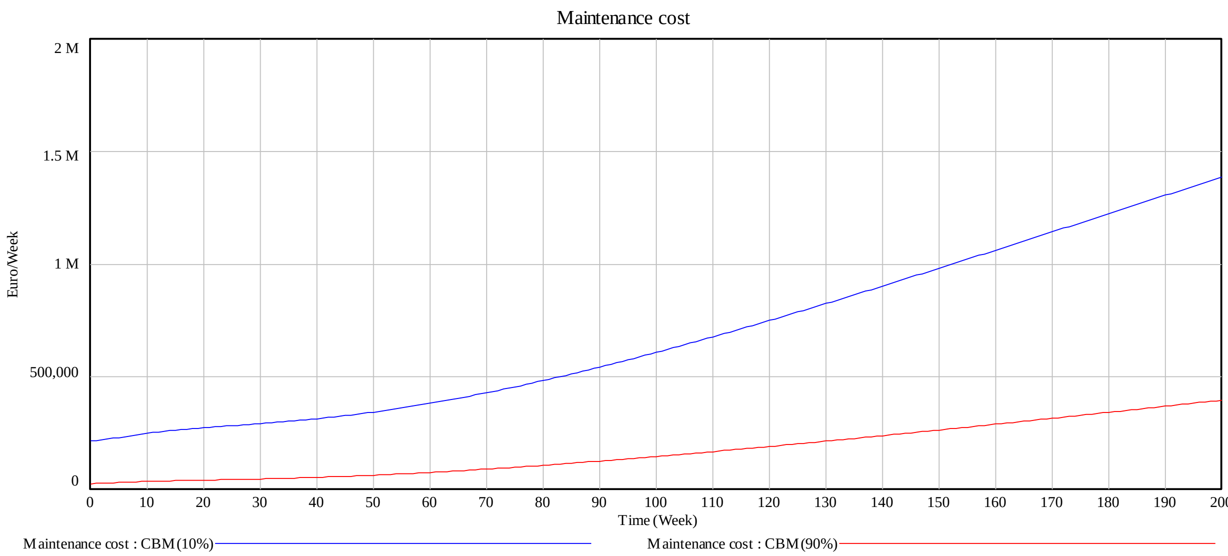

Figure 5. Scenario analysis result for "Maintenance cost" (the OEM)

"Sales cost" hasn't changed among two scenarios, as they have the same amount of sales representatives and training costs. In summary, both two sources of "Revenue" are improved; "Machine making cost" is increased, but due to the increase of "Sales revenue, its increase will not hurt the margin; "Maintenance cost" is significantly decreased; and "Sales cost" remains constant. All in all, these lead to an 11.1% increase in "Cumulated Margin" (195,590,000 euro) for the OEM, which is shown in Figure 6.

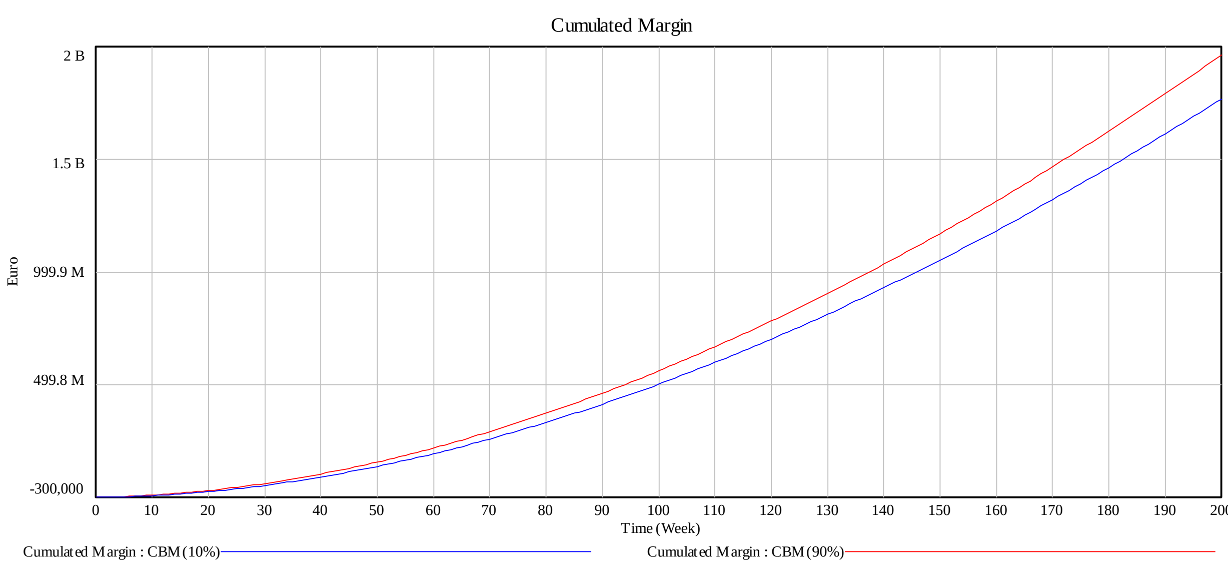

Figure 6. Scenario analysis result for "Cumulated Margin" (the OEM)

Model for the OEM's customer

Three departments (i.e. sales, operations, and finance) are involved in the model for the OEM's customer (Figure 7). Again, "Cumulated Margin" is determined by the speed of both "Revenue" increase and "Cost" consumption. Both "Revenue" increase and "Cost" consumption are decided by "Activity level", which is influenced by "Sales volume" with certain lead time for continuous improvement and learning. The increase of "CBM percentage" can directly affect "Sales volume" in a short run. Its impact can also be indirect, through the improvement of "Activity reputation" with a long lead time (from "being good" to "being known" to gain premium). Figure 8 shows our scenario analysis result for the "Cumulated Margin" of the OEM's customer. Thanks to the increase of "CBM percentage", the "Cumulated Margin" of the OEM's customer will improve 9.2% (716,950,000 euro) in the end of our simulation (in Week 200).

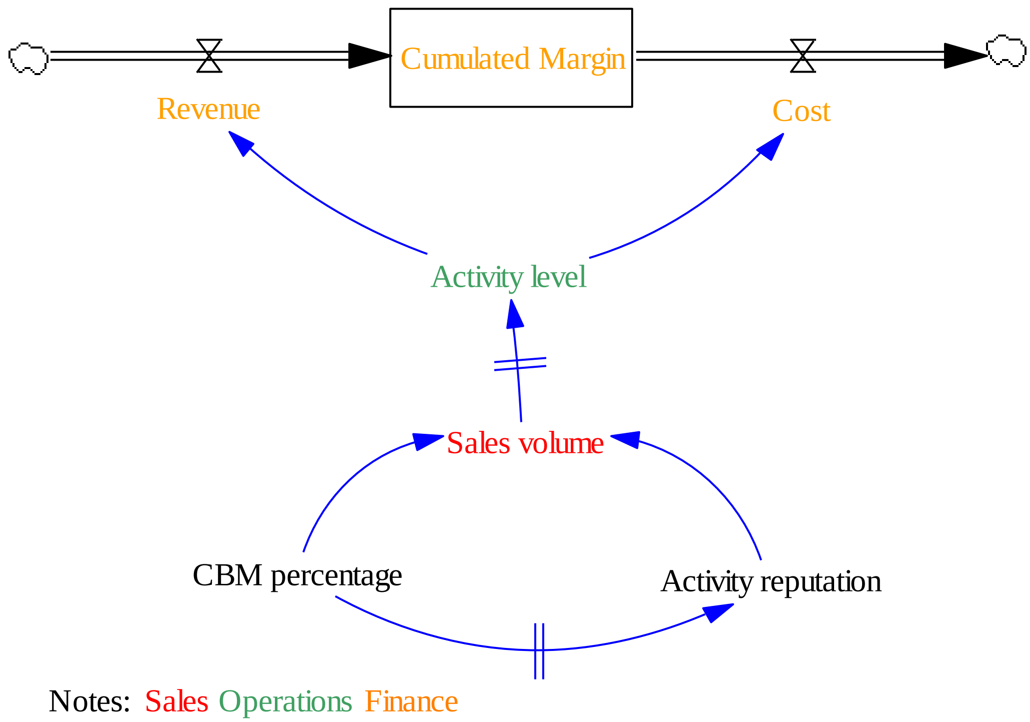

Figure 7. Model illustration (the OEM's customer)

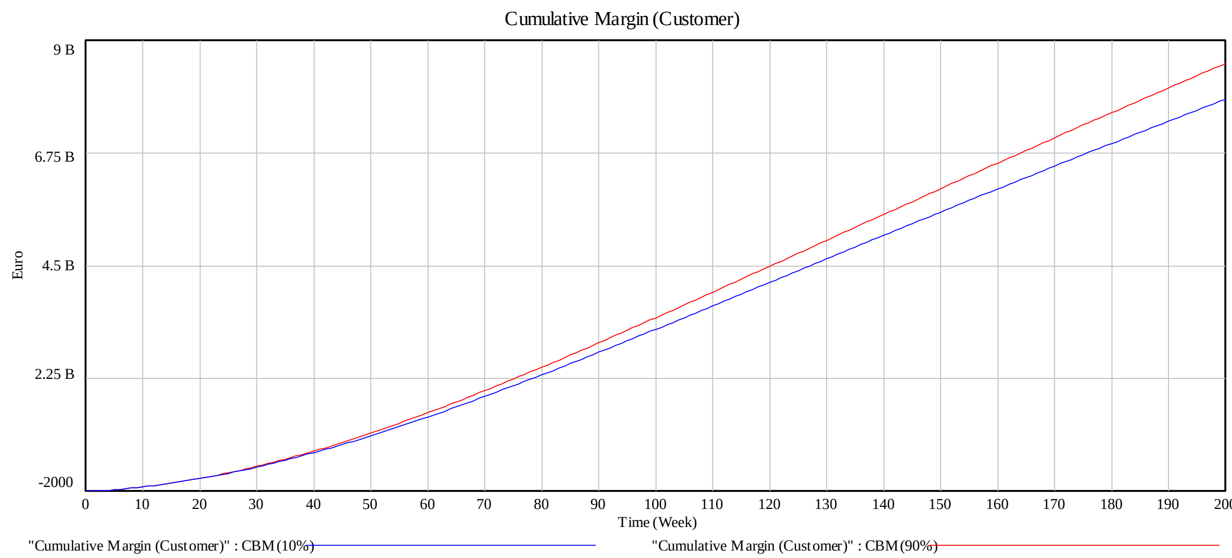

Figure 8. Scenario analysis result for "Cumulated Margin" (the OEM's customer)

Sensitivity analysis

To test the robustness of our results, we further apply sensitivity analysis on four variables: “Failure time” (determines “Failure rate”), “Diagnose time” (determines “Diagnose rate”), “Corrective maintenance time” (determines “Corrective maintenance rate”), and “CBM time” (determines “CBM rate”), as they are all directly related to the change from corrective maintenance to CBM.

In our model for the OEM, “Failure rate” describes the speed that “Machine in warning” turns to “Machine in failure”. “Failure rate” is determined by “Failure time”. In our base scenarios, the “Failure time” is set as 10 weeks, meaning that for every 10 weeks there is 1 “Machine in warning” turning to “Machine in failure”. The sensitivity analysis results for “Failure time” are shown in both Table 1 and Figure 9. We clearly see a tipping point (around 9 weeks), after which a short “Failure time” will significantly influence CBM practices. This is a challenge for the R&D engineers, as they should ensure that the “Machine in warning” can still work for a long time (9 weeks plus) before it is taken CBM.

Table 1. Sensitivity analysis results for “Failure time”

Failure time (weeks)	12	11	10 (base)	9	8
The OEM	10.7%	10.9%	11.1%	11.3%	0.5%
OEM's customer	8.1%	8.6%	9.2%	9.8%	0.9%

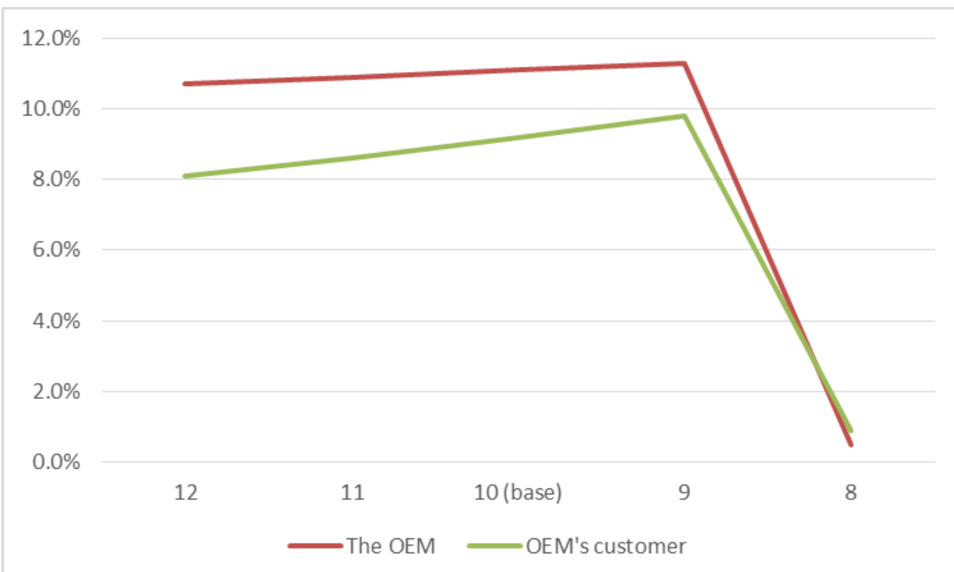

Figure 9. Sensitivity analysis results for “Failure time”

In our model for the OEM, “Diagnose rate” describes the speed that potential problems are identified from “Machine in operation”, so that it turns to “Machine in warning”. “Diagnose rate” is determined by “Diagnose time”. In our base scenarios, the “Diagnose time” is set as 10 weeks, meaning that potential problems can be diagnosed in 10 weeks. The sensitivity analysis results for “Diagnose time” are shown in both Table 2 and Figure 10. The results are in line with our expectation that the shorter the “Diagnose time”, the better the CBM performance for both the OEM and its customer.

Table 2. Sensitivity analysis results for "Diagnose time"

Diagnose time (weeks)	12	11	10 (base)	9	8
The OEM	9.7%	10.3%	11.1%	12.0%	13.1%
OEM's customer	7.6%	8.3%	9.2%	10.2%	11.6%

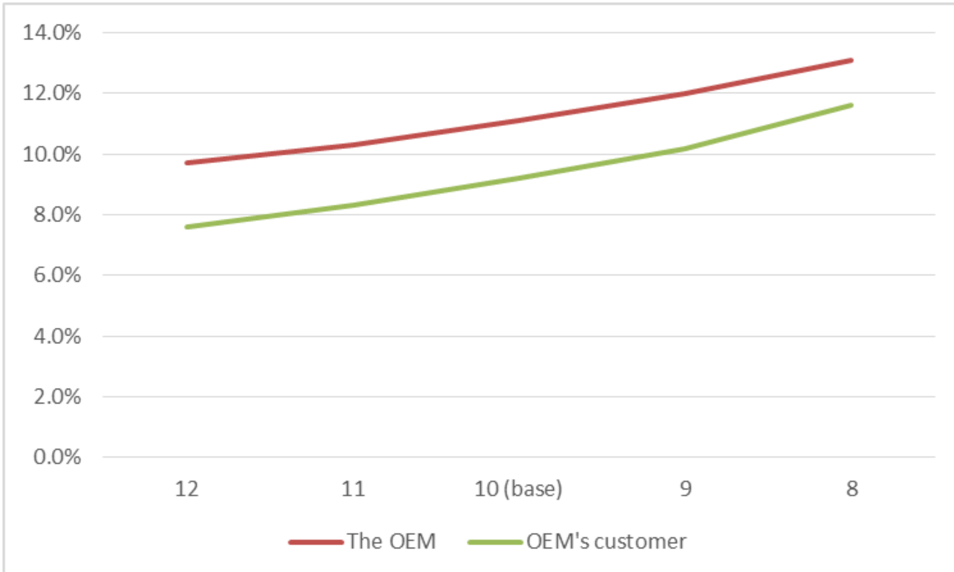

Figure 10. Sensitivity analysis results for "Diagnose time"

In our model for the OEM, "Corrective maintenance rate" describes the speed that a corrective maintenance is delivered by engineers, so that "Machine in failure" turns back to "Machine in operation". "Corrective maintenance rate" is determined by "Corrective maintenance time". In our base scenarios, the "Corrective maintenance time" is set as 1 week, meaning that a corrective maintenance can be finished in 1 week. The sensitivity analysis results for "Corrective maintenance time" are shown in both Table 3 and Figure 11. The results are in line with our expectation that the longer the "Corrective maintenance time", the better the CBM performance for both the OEM and its customer. And the influence on the OEM's customer is more sensitive. Therefore, if "Corrective maintenance time" is rather long at the beginning, it is much easier for the OEM to persuade its customer to choose more CBM practices.

Table 3. Sensitivity analysis results for "Corrective maintenance time"

Corrective maintenance time (weeks)	0.2	0.6	1 (base)	1.4	1.8
The OEM	3.2%	9.0%	11.1%	13.7%	16.5%
OEM's customer	1.9%	5.5%	9.2%	13.2%	17.4%

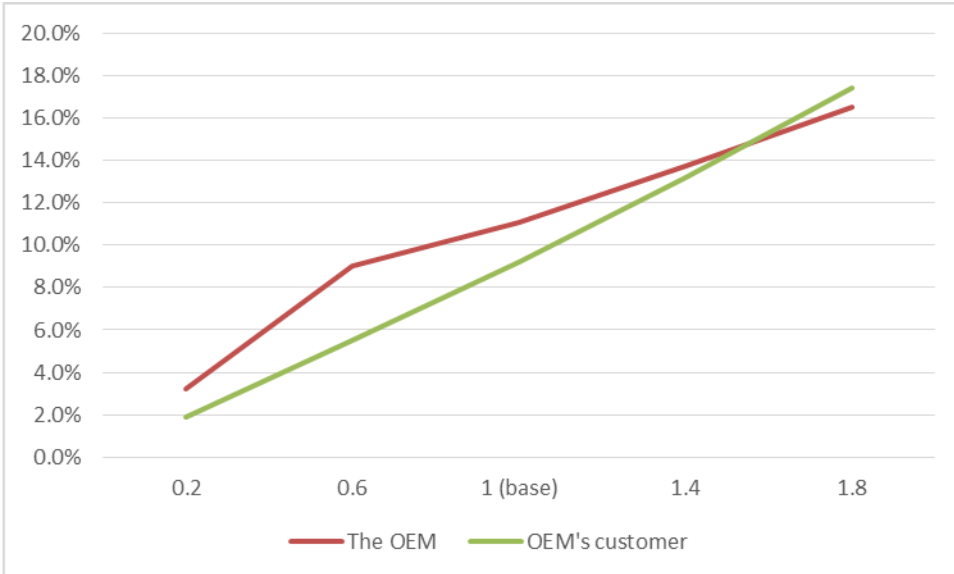

Figure 11. Sensitivity analysis results for “Corrective maintenance time”

In our model for the OEM, “CBM rate” describes the speed that a CBM is delivered by engineers, so that “Machine in warning” turns back to “Machine in operation”. “CBM rate” is determined by “CBM time” (together with “CBM percentage”). In our base scenarios, the “CBM time” is set as 1 week, meaning that a CBM can be finished in 1 week. The sensitivity analysis results for “CBM time” are shown in both Table 4 and Figure 12. At the first glance, the results are counter-intuitive, as shorter “CBM time” leads to worse CBM performance. However, through a post hoc check, we find that CBM performance (“Cumulated Margin”) is increased for both Océ and its customer, when “CBM time” becomes shorter. Our perception is actually from the decrease of improvement percentage, which means that the improvement of “CBM time” will receive less and less return. Therefore, the OEM needs to hold a balanced view when investing in the improvement of “CBM time” and also thinks about how to explain such situation to its customer.

Table 4. Sensitivity analysis results for “CBM time”

CBM time (weeks)	1.8	1.4	1 (base)	0.6	0.2
The OEM	12.6%	12.1%	11.1%	9.3%	5.6%
OEM's customer	11.7%	10.6%	9.2%	7.1%	3.4%

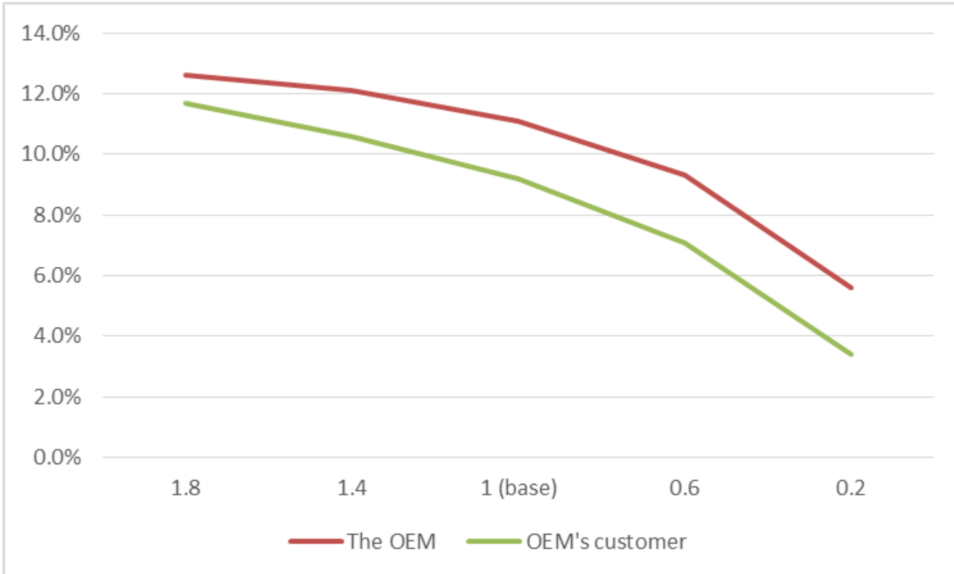

Figure 12. Sensitivity analysis results for “CBM time”

Conclusion

Through system dynamics modeling, we prove that CBM practices can benefit both the OEM and its customers. An estimation of performance improvements for both the OEM and its customer is given in our scenario analyses. About 10% increase for both the OEM and its customer warrants a promising future. Meanwhile, through model illustration as well as the report of scenario analysis results, managers from different departments can understand the dynamic behavior of CBM through their interactions (i.e. organizational complexity) and the lead time involved (i.e. dynamic complexity). Our findings are in line with Repenning & Sterman (2002) that the critical determinants of success in efforts to learn and improve processes (i.e. activities to improve the performance of CBM practices in our case) are the interactions between managers’ attributions about the cause of performance change and the physical structure of the workplace, particularly delays between investing in improvement and recognizing the rewards.

We have further applied four sensitivity analyses to test the robustness of our scenario analysis results. Our sensitivity analysis results suggest that: (1) The R&D engineers should guarantee that the “Machine in warning” can still work for a long time (“Failure time” should be more than 9 weeks) before it is taken CBM. (2) The R&D engineers’ efforts on shortening “Diagnose time” can moderately help with CBM practices. (3) If “Corrective maintenance time” is rather long at the beginning (more than 1 week), it is much easier for the service department of the OEM to persuade customers to choose more CBM practices. (4) The financial department of the OEM needs to hold a balanced view when investing in the improvement of “CBM time”, and the sales department of the OEM needs to think about how to explain the slowing down of performance increase to its customers.

References

Ahmad, R., & Kamaruddin, S. (2012). An overview of time-based and condition-based maintenance in industrial application q. *Computers & Industrial Engineering*, *63*(1), 135–149. https://doi.org/10.1016/j.cie.2012.02.002

Akkermans, H., Bogerd, P., & van Doremalen, J. (2004). Travail, transparency and trust: a case study of computer-supported collaborative supply chain planning in high-tech electronics. *European Journal of Operational Research*, *153*(2), 445–456. https://doi.org/10.1016/S0377-2217(03)00164-4

Bhamu, J., & Sangwan, K. S. (2014). Lean manufacturing: literature review and research issues. *International Journal of Operations and Production Management*, *34*(7), 876–940. https://doi.org/10.1108/IJOPM-08-2012-0315

Hyland, P. W., Soosay, C., & Sloan, T. R. (2003). Continuous improvement and learning in the supply chain. *International Journal of Physical Distribution & Logistics Management*, *33*(4), 316–335. https://doi.org/10.1108/09600030310478793

Jonsson, P. (2000). Towards an holistic understanding of disruptions in Operations Management. *Journal of Operations Management*, *18*(6), 701–718. https://doi.org/10.1016/S0272-6963(00)00040-1

Marseguerra, M., Zio, E., & Podofillini, L. (2002). Condition-based maintenance optimization by means of genetic algorithms and Monte Carlo simulation. *Reliability Engineering & System Safety*, *77*(2), 151–165. https://doi.org/10.1016/S0951-8320(02)00043-1

Peng, Y., Dong, M., & Zuo, M. J. (2010). Current status of machine prognostics in condition-based maintenance : a review. *International Journal of Advanced Manufacturing Technology*, *50*(1), 297–313. https://doi.org/10.1007/s00170-009-2482-0

Repenning, N. P., & Sterman, J. D. (2002). Capacity traps and self-confirming attribution errors in the dynamics of process improvement. *Administrative Science Quarterly*, *47*(2), 265–295.

Rindova, V. P., Williamson, I. O., Petkova, A. P., & Sever, J. M. (2005). Being good or being known: An empirical examination of the dimensions, antecedents, and consequences of organizational reputation. *The Academy of Management Journal*, *48*(6), 1033–1049. https://doi.org/10.5465/AMJ.2005.19573108

Thun, J.-H. (2006). Maintaining preventive maintenance and maintenance prevention: analysing the dynamic implications of Total Productive Maintenance. *System Dynamics Review*, *22*(2), 163–179. https://doi.org/10.1002/sdr