Exploring Patterns of Process Improvement with a Generic Model

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Abstract: *Building upon previous work in the field of system dynamics, a generic model of multiple improvement initiatives is outlined. The current model structure incorporates empirical data gathered by the author. The empirical data is taken from a large international survey of manufacturing plants and serves as calibration sets for several program implementation patterns. Statistical analyses and simulation experiments revealed noticeable preliminary results: (i) plants should strive for balanced implementation patterns that focus on multiple programs instead of favoring a single program. (ii) Plants should balance their implementation patterns according to the organizational and technological complexity of the improvement programs, i.e. that comparatively more efforts should be spent on more challenging improvement efforts. The value of the conducted approach lies (i) in the explicit investigation of the impact of different improvement programs (e.g. TQM, TPM, process automation, training) and (ii) in the integration of empirically gathered data.*

Introduction

In spite of its early entry into system dynamics, the concept of generic structures is still developing. Based on Forrester's notion of "general purpose models" (Forrester 1961: 313), the concept of generic structures has evolved mainly into the branches of quantitative and qualitative models (Coyle 2000; Liehr 2004, 2001). The former type includes "generic (canonical) situation models" and "abstracted micro-structures", the latter "counterintuitive system archetypes" (Lane and Smart 1995). Forrester's "Market Growth as Influenced by Capital Investment" (1968) or Lyneis' "Corporate Planning and Policy Design" (1988) are examples of generic models. They are the formal representation of a problem and structure common to many situations. These models—contrary to micro structures—are not designed as building blocks for larger models. Micro structures differ from generic models in both the extent of their structure and their transferability into other contexts. Due to their high aggregation, they can be applied to other situations as building blocks. Micro structures can be classified into those, which serve as building blocks to structures from certain areas and into those, which are applicable in many different contexts (Paich 1985). As building blocks of systems, micro structures can facilitate understanding of complex interactions in social systems (Milling 1972). The second branch of generic structures—system archetypes—are basing mainly on Meadows's (1982: 98) "persistent, system-dependent malfunctions" and on Senge's (1994) monograph "The Fifth Discipline". Especially Senge emphasizes the generic characteristics of his nine archetypes which can provide an explanation to counterintuitive behavior in different contexts. The value of system archetypes lies especially in their limited extent and their transferability to recurring system behaviors. In the following, qualitative or quantitative approaches on process improvements are outlined:

Qualitative approaches: Carrol, Sterman, and Marcus (1997) use a case study at Du Pont for their investigation on the implementation of maintenance programs (e.g. total productive maintenance; TPM, see Nakajima 1988). They use a qualitative system thinking approach without explicit system dynamics modeling, although they use level-rate-diagrams for model illustration (cf. Sterman 2000: chap. 2.4). They outline a typical fixes-that-fail-archetypical behavior, i.e. that less preventive maintenance activities increase productivity in the short run but decrease in the long run, due to the increasing equipment downtime. Repenning and Sterman (2001), Keating et al. (1999), Repenning and Sterman (1997) as well as Oliva, Rockart, and Sterman (1993) abstract from specific improvement programs and analyze process improvement programs more generally with system thinking as methodology. All four articles base on case studies from multiple improvement programs examined at different sites. Beside other valuable findings, they outline that improvement initiatives can facilitate subsequent improvement efforts, if they are evaluated as successful by both managers and workers. However, the same interrelation also can hinder continuous process improvement in the case of low perceived success. Kim (1993) provides two case studies upon process improvement programs (total quality management [TQM] and product development management) in which Senge's system archetypes have been applied in order to facilitate organizational learning.

Quantitative approaches: In a case study, Sterman, Kofman, and Repenning (1997) analyze the TQM program at Analog Devices. As far as the author is aware of, they provide the only fully documented and publicly available system dynamics analysis of an improvement program (for documentation, see Repenning and Sterman 1994). In their case study with Analog Devices they revealed that due to Analog's TQM program the productivity grew faster than customer demand and thus did generate excess labor capacity and massive layoffs. The authors provide an extensive model which is highly specific to the Analog case. In spite of the great value of their work to management literature, the transferability of the model is therefore limited. Other formal modeling approaches on process improvement programs have been conducted by Repenning (2002, on TQM) and Maier (2004; 2000, both on TPM). Even though both authors provide mathematical equations to some model interrelations, they do not include a complete model listing.

Building upon both qualitative and quantitative approaches, a generic model of multiple improvement initiatives is outlined. Existing micro structures are applied as building blocks where possible (e.g. from Hines 2005, Sterman 2000, Repenning and Sterman 1994, and Lyneis 1988). The model is intended to provide insights in several program implementation patterns which are gathered from empirical data by the author. This is necessary as plants exhibit different implementation patterns, i.e. they focus equally on several programs or favor single programs. Empirical analyses conducted by the author show, that the mode of implementation pattern exhibits a great impact on plant performance. Therefore, different types of improvement programs are incorporated explicitly into the model. The current model structure presented in this article incorporates the preliminary results of an ongoing research project. The model is intended to integrate data from empirical analyses with the system dynamics approach. Simulation experiments conducted on the current model structure have revealed noticeable and encouraging results. In the next section, empirical findings are discussed. In the subsequent section, the model structure is introduced. Special attention is given to the integration of empirical data into the model. The article ends with a discussion of the simulation results and with an outlook on subsequent research.

Empirical analyses on the impact of multiple improvement programs

In the following, two empirical analyses conducted by the author are outlined and compared. The first analysis investigates the impact of Total Quality Management (TQM) programs on plant performance. This is done due the prominent statues of TQM in system dynamics literature (e.g. Kim 1993; Sterman, Kofman, and Repenning 1997; Keating et al. 1999). In the second analysis, the scope is broadened to cover multiple improvement programs. The statistical investigations are based on data gathered in the third iteration of the 'International Manufacturing Strategy Survey' (IMSS-III). In the study, 465 manufacturing plants from 14 countries were investigated (Laugen et al. 2005; Größler and Grübner 2006).

Improvement programs
*Updating process equipment (**pro. equip.**)* *Expanding manufacturing capacity (**man. capac.**)* *Engaging in process automation (**autom.**)* *Quality improvement and control (**TQM**)* *Equipment productivity (**TPM**)* *Delegation and knowledge of workforce (**deleg. & knowl**.)* *Environment, workplace safety and healthy (**saf. & heal.**)*

Table 1: Manufacturing improvement programs in IMSS-III

Factors	**Items** ***"Improvements over the last three years in…"***	**Factor Loadings [T-Values]**
Quality	*Manufacturing conformance* *Product quality and reliability*	0.78 [11.36] 0.65 [10.24]
Time	*Delivery speed* *Delivery reliability* *Manufacturing lead time*	0.75 [15.17] 0.82 [17.03] 0.52 [10.10]
Flexibility	*Volume flexibility* *Mix flexibility*	0.84 [12.52] 0.57[10.62]
Costs	*Labor productivity* *Inventory turnover* *Capacity utilization* *Overhead costs*	0.63 [11.57] 0.53 [9.42] 0.60 [10.47] 0.42 [7.36]
Reliability measures: χ^2 = 87.42; degrees of freedom = 38; P-Value = 0.00001; RMSEA = 0.055		

Table 2: Building factor variables of Quality, Time, Flexibility, and Costs

Beside other aspects regarding plants' manufacturing strategies, improvement programs are explored in the IMSS-III survey. Table 1 shows the programs that are related to the area of manufacturing; other programs for example on new product development or on information technology are neglected in this article. In order to test plant performance, the factors *Quality*, *Time*, *Flexibility*, and *Costs* are build in a confirmatory factor analysis with LISREL ('LIneral-Structual-RELatoinships', Jöreskog and Sörbom 1979). In the field of manufacturing strategy it is common understanding that plant performance can be measured with these four basic dimensions (Ward, Bickford, and Leong 1996; Größler and Grübner 2006; Größler 2005). The building factors of plant performance are outlined in Table 2. The performance factors exhibit high loadings and appropriate measures of reliability.

Sterman, Kofman, and Repenning (1997) find that plants engaged in TQM programs yield better results in measures of quality but suffer paradoxically from high costs and financial stress. These findings—i.e. plants with many TQM activities do not necessarily yield lower costs—can be underpinned on the IMSS data, if the impact of TQM on plant performance is explored. As shown in Figure 1, the IMSS data is clustered regarding the degree of TQM implementation in *TQM-high* and *TQM-low* implementers. The performance figures of the TQM-high implementers are decreasing comparatively from quality, over time and flexibility, to costs; the latter measure is only slightly above the average. (All graphs are based on standardized five-points-Likert-scales, thus zero equals the average and plus/minus one equals the average plus/minus the standard deviation). It is also noticeable that the implementation patterns of TQM-high and TQM-low implementers only differ significantly regarding TQM. The other programs do not diverge much from their mean values:

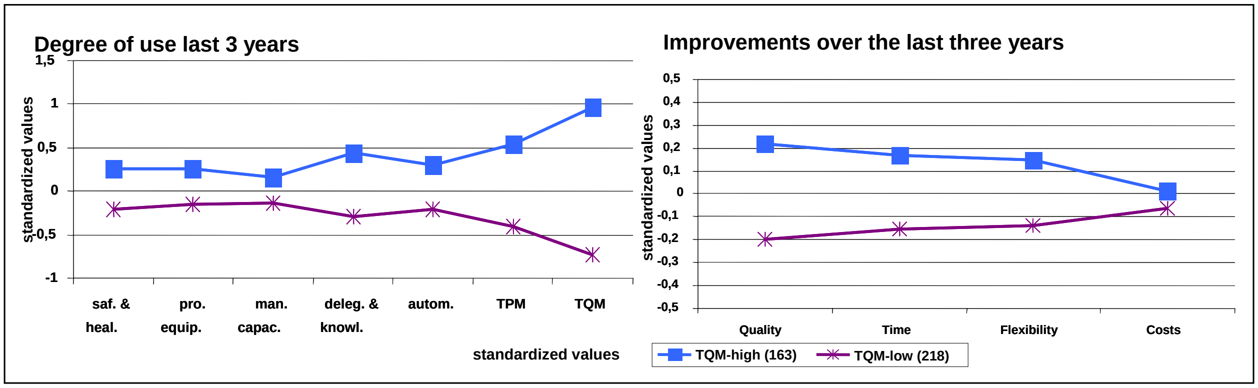

Figure 1: Implementation clusters and plant performance measures regarding Total Quality Management implementation (cluster analysis I)

However, different patterns can be revealed if a broader scope is applied that covers all manufacturing improvement programs. Figure 2 displays the different implementation groups, if the IMSS data is clustered regarding the implementation of all manufacturing improvement programs (not just TQM as in the cluster analysis before). This cluster analysis finds three distinguishable implementation groups—*high-*, *medium-* and *low-implementer*. It is interesting to notice that the group of overall high implementers outperforms the TQM-high cluster in every performance criterion, even in quality (0.29 vs. 0.22) although the former group conducts comparatively fewer activities of quality improvement and control (0.82 vs. 0.96). The overall high implementers also achieve higher relative payoffs from the conducted improvement efforts than the TQM-high cluster, even in TQM (0.68 vs. 0.56, see Figure 3).

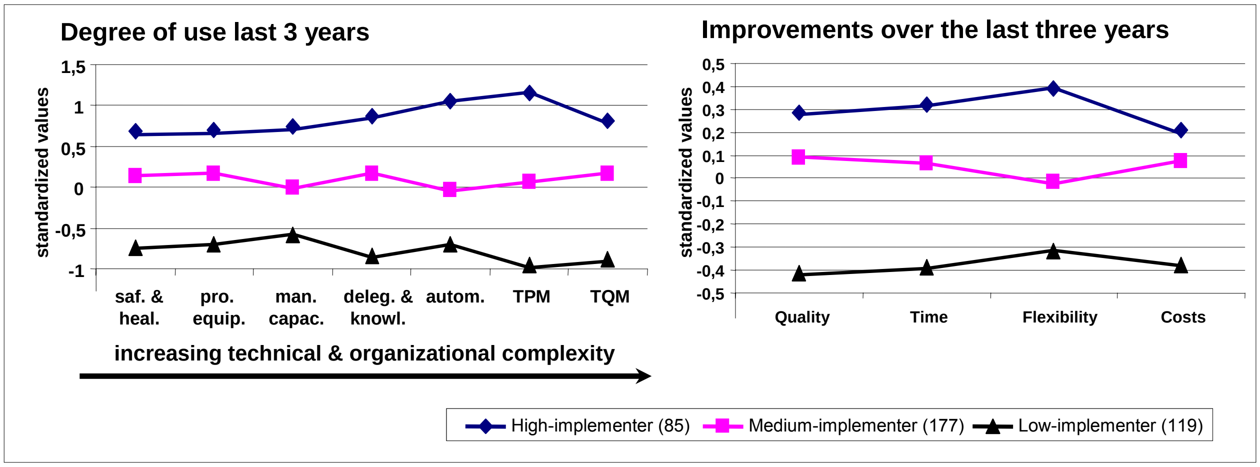

Figure 2: Implementation clusters and plant performance measures regarding the implementation of all improvement programs (cluster analysis II)

The performance figures of the high-implementer cluster do not show the same 'unbalanced' performance pattern as those of the TQM-high group in the first analysis. But the High-implementer group exhibits comparatively high flexibility and low costs measures. This is in accordance to Größler and Grübner (2006) who find a trade-off relationship between flexibility and costs, which means that one can only improve in return for the other dimension to decline. However, the cluster of high implementing plants yields significant higher performance in costs than the average or the other clusters. Thus, an 'improvement paradox'—i.e. plants yield high measures in quality due to process improvement programs but exhibit low performance in costs—can be confirmed in the first analysis regarding TQM but not in the second analysis that investigates the impact of multiple improvement programs on performance. The second analysis rather underpins that plants which conduct multiple programs at the same time yield higher performance figures. Thus, plants should not strive for a single program like TQM.

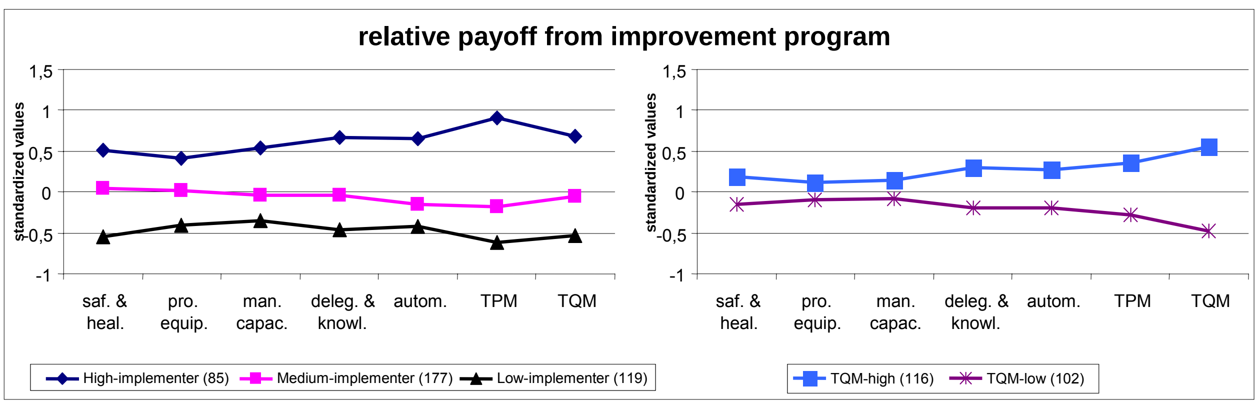

Figure 3: Comparison of relative payoffs of overall and TQM-implementing clusters

However, it is also noticeable that the implementation pattern of the high-implementing group exhibits an upward slope, if the programs are arranged in respect of their technical and organizational complexity (see Figure 2). The programs are arranged according to Schneiderman's (1999, 1988) Half-Life/Complexity Matrix. Schneiderman's matrix is very useful to provide an estimate or a benchmark for goal setting within the scope of an improvement initiative. The matrix is based on empirical analyses of many different improvement efforts conducted by experienced improvement teams. Schneiderman (1988) found in his investigation that experienced improvement teams maintain a constant improvement rate, i.e. the level of defects exhibits a similar behavior as radioactive decay, which means that the amount of time necessary for a level of defects to drop by 50% is constant. Thus, the level defects can be calculated at a particular time *t* with

$$(1:) \quad Y - Y_{\min} = (Y_0 - Y_{\min})\exp(-\phi(t - t_0)) \qquad \text{and} \qquad \phi = \frac{\ln(2)}{t_{HL}}$$

where Y_{min} equals the minimum defect level achievable theoretically, Y_o equals the initial defect level, t equals time, t_o equals initial time, and t_{HL} equals the defect half life (Schneiderman 1988: 53). In addition, Schneiderman revealed that the constant half-life time (t_{HL}) increases according to organizational and technical complexity of the improvement effort. Schneiderman found that initiatives which place in the left bottom part of the matrix in Figure 4 exhibit half-life times of approximately one month and in the right upper part of twenty-two months. TQM, for example, involves people from different functions or even different organizations (e.g. suppliers) and thus possesses high organizational complexity. Contrary to that, updating of process equipment (*pro. equip.*) implies cooperation of a few different departments and functions and therefore exhibits a low organizational but medium technical complexity. The dimension of technical complexity grasps the novelty of the applied technology and therefore—for example—automation (*autom.*) features higher technical complexity than improvements in delegation and knowledge of workforce (*deleg. & knowl.*). The adopted Schneiderman-Matrix is illustrated in Figure 4:

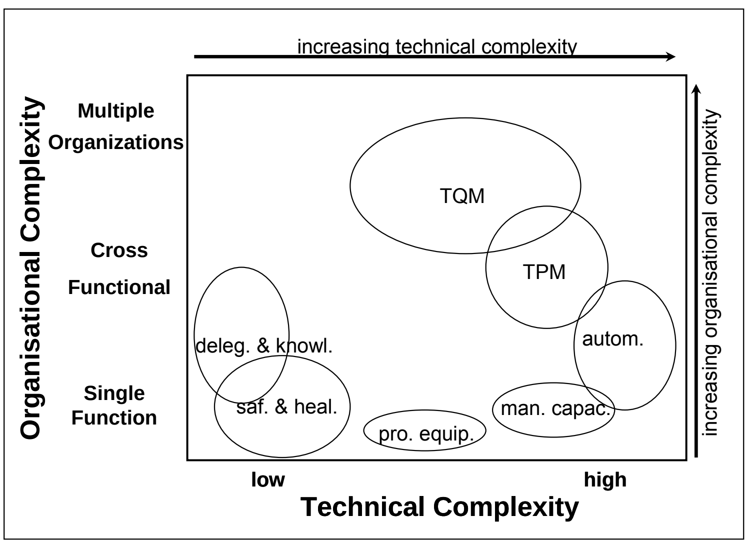

Figure 4: The Half-Life/Complexity Matrix adapted from Schneiderman 1999, 1988)

The sizes of the ellipses contribute to the fuzziness of the improvement programs, which makes it difficult to give a definite measure of technical and organizational complexity. For example, a manufacturer which has recently been visited by the author subsumes nearly every continuous improvement effort under the acronym TPM. Thus, TPM can differ significantly in both dimensions from one manufacturer to another. This is even more the case with TQM, which might include suppliers and new technology but can also be completely internal and with available equipment.

The concept of improvement half-life times is quite promising as it gives a theoretical underpinning for the findings illustrated in Figure 2. Due to increasing half-life times, a plant has to allocate more efforts in complex than in simple programs in order to achieve 'balanced' improvement rates. For example, improvements due to automation (*autom.*) can be achieved rather easily. Automation contributes extensively to labor productivity but only little to stimulation of demand. Therefore, high improvement rates in automation can lead to excess capacity if demand is not increasing with the same rate. Thus, plants should also engage in improvement efforts that upgrade the plant's performance in 'order winning' criteria, like time and flexibility (Hill 2000). Lower costs due to higher productivity might not be sufficient to generate higher demand, if price is just an 'order qualifying' criteria. It can be argued that the high-implementing plants were able to maintain a more or less balanced improvement pattern with comparatively high achievements on all performance figures. Schneiderman (1999) also emphasizes that the half-life times outlined in his matrix can only be achieved by an "'experienced' improvement team" and that not every plant will be able to achieve such improvement rates right from the start. He suggests that plants with low experiences in process improvements should start with less complex initiatives which can contribute to organizational learning (cf. Stata 1989). Gains in process improvement experiences facilitate the plant's capabilities to handle higher organizational and technical complexity, and from that the plant can challenge more ambitious improvement efforts. In this regard, the comparatively increasing complexity in implementation patterns between the three clusters is comprehensible (see Figure 2).

A generic model of multiple process improvement efforts

In the following, preliminary results of an ongoing system dynamics modeling project are outlined. The empirical findings will serve for both calibration and validation of the model. Figure 5 gives a brief overview of the model structure:

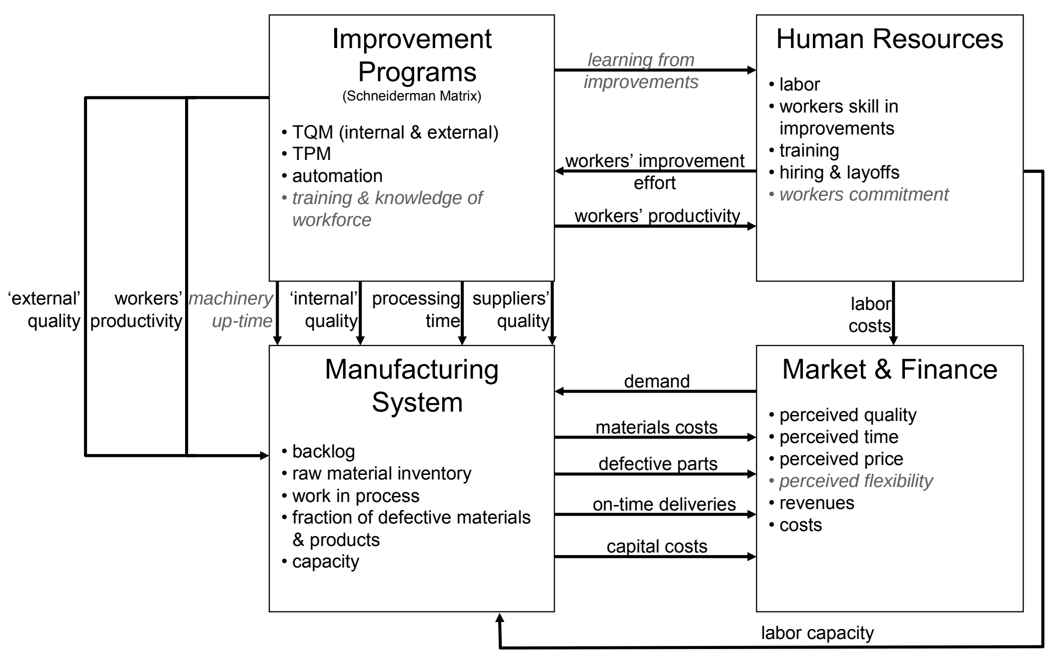

Figure 5: Overview of model structure

As mentioned before, the modeling project has not been completed yet. The interrelations and variables which are not implemented in the current state are highlighted in italics. The model in its current state is build out of four sectors:

Improvement programs (see Figure 7): Schneiderman's Half-life-Matrix forms the main building block in this sector (cf. Sterman, Kofman, and Repenning 1997) and serves as an interface to empirical data. From Equation (1) it follows:

$$\frac{dY}{dt} = -\phi(Y_0 - Y_{\min})\exp(-\phi(t-t_0)),\ \frac{Y - Y_{\min}}{Y_0 - Y_{\min}} = \exp(-\phi(t-t_0)),\ \text{and}\ \phi = \frac{\ln(2)}{t_{HL}},$$

thus, the rate of improvement equals (2:) $$\frac{dY}{dt} = -\frac{\ln(2)}{t_{HL}}(Y - Y_{\min}),$$

where Y_{min} equals the minimum defect level achievable theoretically, Y_o equals the initial defect level, t equals time, t_o equals initial time, and t_{HL} equals the defect half life. Equation (2) represents the improvement rate as observed by Schneiderman (1988). In the model, it serves as a benchmark, which means that this rate can be maintained if the workers are committed and experienced with improvement initiatives. Furthermore, the improvement rate depends on the effort of management towards defects reduction. In order to grasp commitment and the effort of workers and management towards process improvement, equation (2) is supplemented with two factors. The improvement rate of defect level i is therefore:

(3:) $$imp_i = \frac{\ln(2)}{t_{HL\,i}}(Y_i - Y_{\min_i}) * \alpha_i * \beta,$$

where α_i stands for managements' effort for defect level i and β for the commitment and skill of the workforce. In other words, if management is focusing on improvements in defects level i (α_i=1) and workers are as experienced and motivated (β=1) as the improvement teams observed by Schneiderman (1988) the plant will yield the same improvement rate imp_i as outlined in the half-life/complexity-matrix. On the other hand, if management and workers do not spend enough efforts in maintaining process improvement, the defect level deteriorates to it is initial value:

(4:) $$det_i = \frac{\ln(2)}{t_{E\,i}} * (Y_{0_i} - Y_i),\ \text{with defect level } i \text{ equals } Y_i = Y_{0_i} + \int (det_i\text{-}imp_i)\, dt.$$

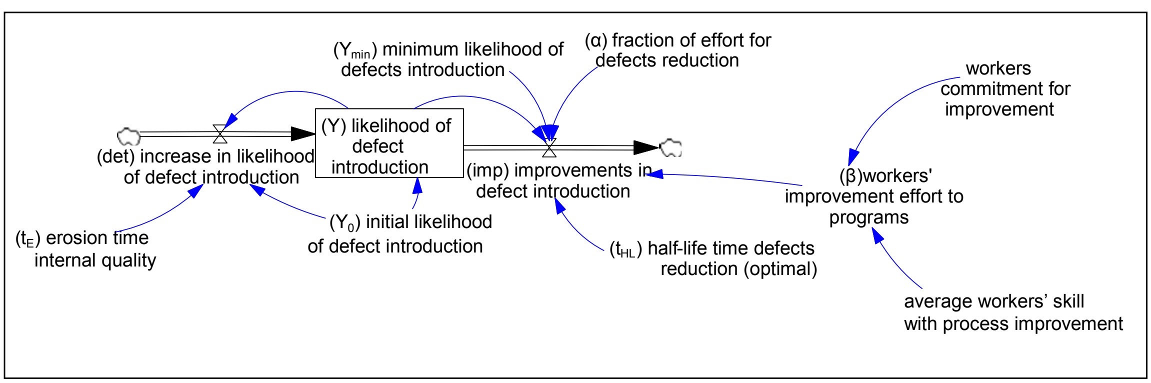

Figure 6: Likelihood of defect introduction

Figure 6 illustrates the stock and flow structure of 'likelihood of defect introduction'. This variable stands for internal TQM, i.e. the failures which are introduced during processing of materials and parts. Improvements are represented with an outflow and deteriorations with an inflow, respectively.

The other improvement initiatives are modeled correspondingly, with specific initial values, half-life times, erosion times, and management efforts towards improvement. In this article, the term ‘defect level’ is used in its most general sense according to Schneiderman (1988: 53), like “errors, rework, yield loss, […] unscheduled downtime, […]cost of poor quality”, and so on. Therefore the other improvement programs are mimicked with ‘processing time’ (automation), ‘fraction of defective materials into inventory’ (external TQM), ‘fraction of machinery downtime’ (TPM), ‘probability of defective parts detection’ (Total Quality Control, TQC), and ‘labor productivity’ (training) (see Figure 7). In order to integrate empirical data into the model, every defect level i is calibrated with its specific half-life time (t_{HL_i}) assessed from Schneiderman (1988) as well as its initial value (Y_{o_i}) and management’s effort towards improvement (α_i) evaluated by empirical data gathered by the author, respectively.

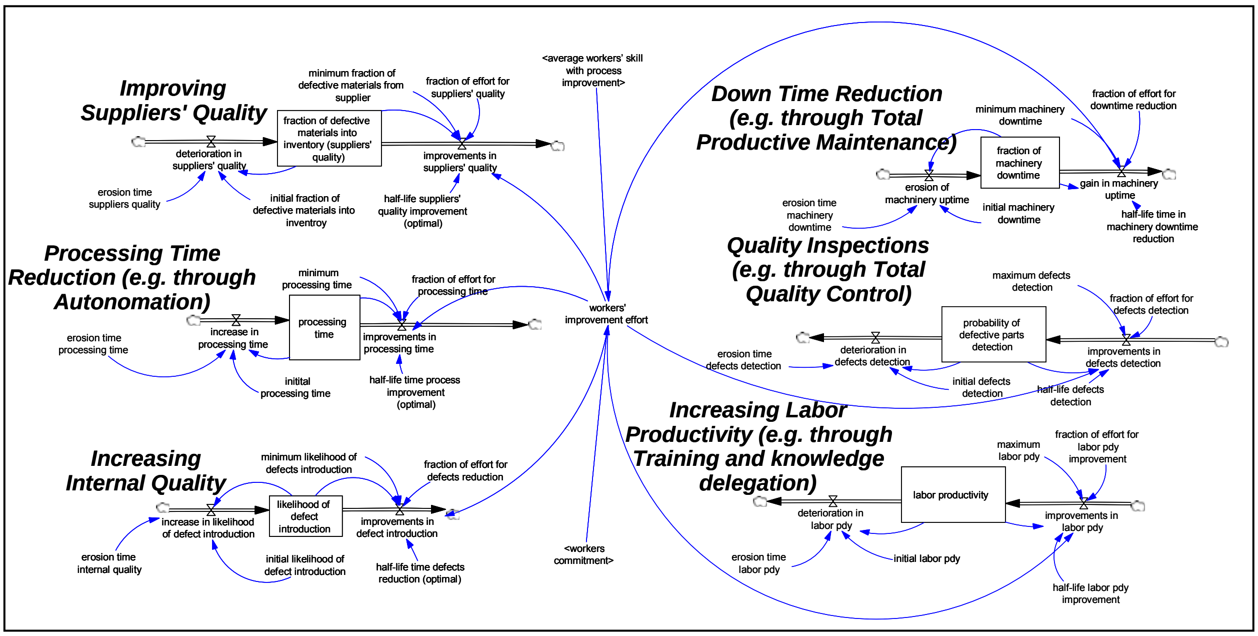

Figure 7: Improvement Program sector

As outlined in Figure 5, the different defect levels are connected to the Manufacturing System and the Human Resource sector. The former sector will be explained briefly in the following:

Manufacturing System (see Figure 8): The Manufacturing System is built as a co-flow structure (Hines 2005; Sterman 2000). In the upper aging chain of the co-flow, materials are processed through the production system: materials delivered from suppliers are stored in ‘raw materials inventory’ and are fed in the production process (‘parts in wip’). The lower aging chain represents materials respectively parts that are defective. Defective materials might be received from a supplier (‘fraction of defective materials into inventory (suppliers' quality)’; external TQM) or might get damaged during the production process (‘likelihood of defect introduction’; internal TQM). Some of the defective parts are detected (‘probability of defective parts detection’; TQC) but some are delivered to the customer (‘fraction of defective parts to customer’), which deteriorates the quality reputation of the plant. In the current state of the model, ‘fraction of machinery downtime’ (TPM) is not included. Orders and production lots are released according to the ‘backlog’ and the ‘desired throughput time’. The ‘desired throughput production rate’ is adjusted with the ‘perceived process capability’, which means that a comparatively high degree of scrap leads to a higher ‘desired production rate’.

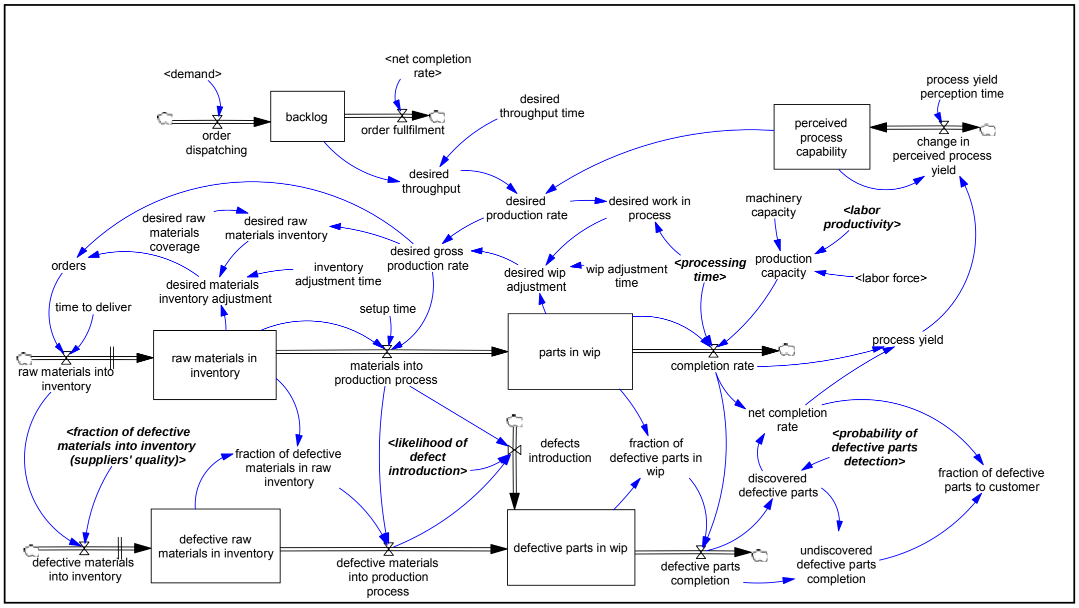

Figure 8: Manufacturing System sector

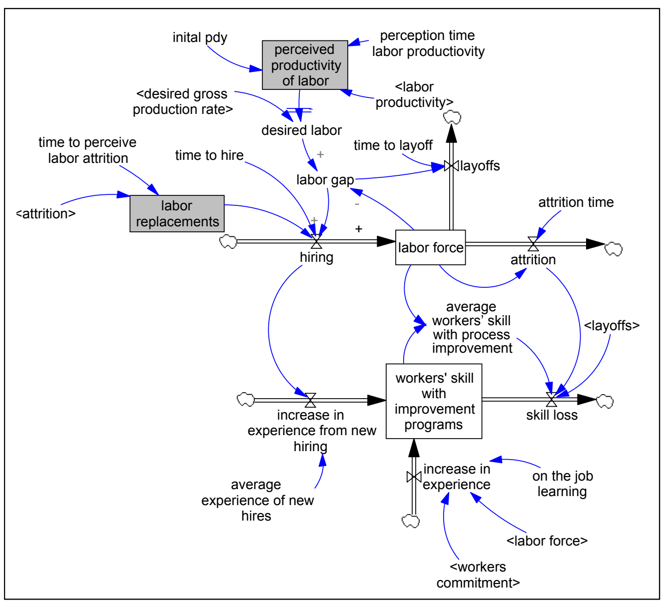

Figure 9: Human Resources sector

Human Resources (see Figure 9): The human resource section is build out of a co-flow structure, too. In the upper aging chain, hiring and laying-off of workers is conducted according to the ‘perceived productivity of labor’ and ‘desired gross production rate’. The latter is derived from customer demand, which means that low (high) workers’ productivity and comparatively high (low) demand leads to hiring (laying-off) of workers. In the current state, workers’ skills depend mainly on on-the job training. However, it is planned to include learning from improvements as well. In the current state, ‘workers commitment’ is set to 1. It is also planned to make this variable endogenous according to perceived layoffs and experiences with process improvement programs.

Market & Finance (see Figure 10): The market and finance sector exhibits three performance figures: 'perceived on-time delivery' for *time*, 'perceived price ratio' for *costs*, and 'perceived quality' for *quality*; a figure for flexibility has not been included yet. As outlined in Figure 5 and Figure 10, 'costs per unit' are calculated out of costs of material, labor and capital. The price is calculated with a fixed profit 'margin'. 'Perceived quality' depends on the perceived 'fraction of defective parts to customer'. 'Perceived on-time delivery' depends on the ratio of actual to desired throughput time. Financial resources are building up through 'revenues' and are declining through 'expenses'.

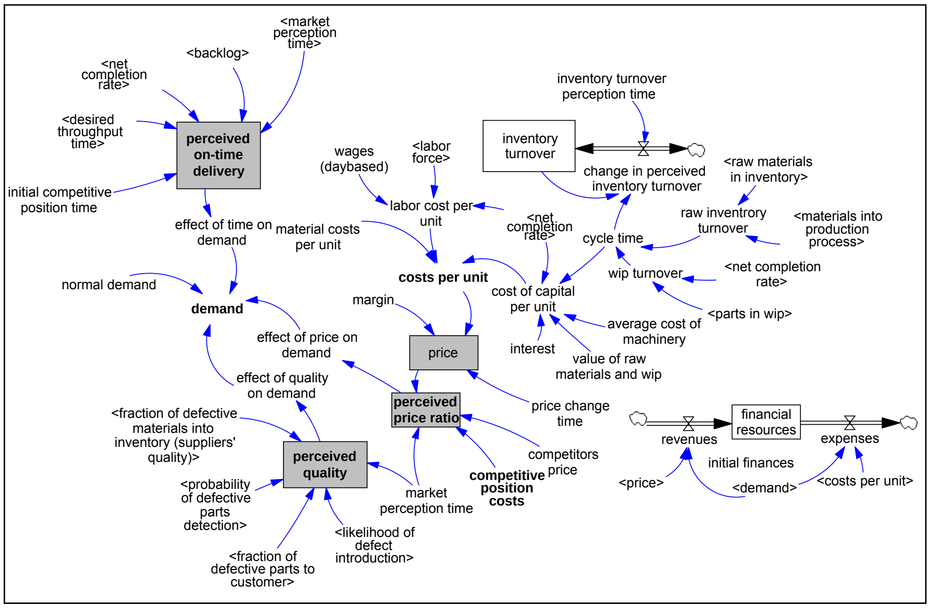

Figure 10: Market & Finance sector

Preliminary results and outlook

In the following, preliminary simulation results carried out on the current model structure are outlined. In the current state, the model does not exhibit an interconnection between improvement initiatives and learning from improvements. Therefore, workers' commitment and skill in process improvement do not change endogenously due to perceived success or failure of improvement initiatives. However, it is planned to include this relationship. Figure 11 illustrates the simulation runs of high- and low-implementers, initialized according to empirical data (e.g. high-implementer plants possess approx. 15% better initial values than low-implementer plants.) Workers' effort for improvement programs stays at the same level in the several runs in Figure 11. Furthermore, both simulated groups maintain a 'balanced' implementation pattern with the same amount of effort to every program. The equilibrium runs illustrate the situation, if the defect levels are maintained at their initial states:

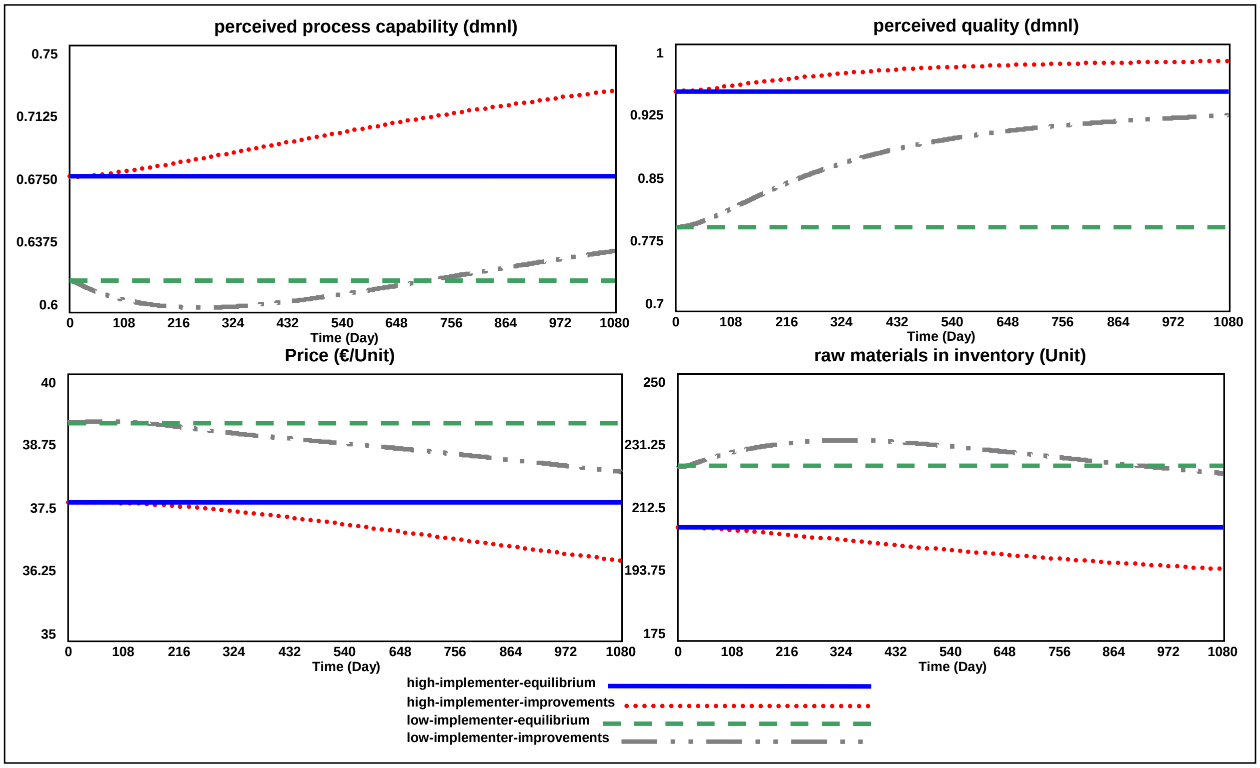

Figure 11: Simulation runs of high and low implementers——equal workers' commitment and skill——balanced implementation pattern

The low-implementer-improvement run shows a worse-before-better-effect which is due mainly to the different half-life times of the improvement programs (see e.g. 'perceived process capability' in Figure 11). This is the case as improvements in defects detection and automation possess lower half-life times than achievements in internal and external TQM (in the model, defects detection half-life is 2.2 and external TQM is 22 months, c.f. Schneiderman 1988). Thus, failure generation due to insufficient quality standards improves more slowly than the elimination of defective parts. Therefore, 'net completion rate' falls *ceteris paribus* in the short run due to the elimination of scrap, which would have been delivered to the customer otherwise. As a result, 'perceived quality' rises steadily due to elimination of defective parts. However, inventories in the low-implementer-improvement simulation setting are rising in the short run due to higher quality. This is a counterintuitive effect as one would expect that fewer inventories are needed in the event of higher quality, as it is the case in the high-implementer-improvement setting. The desired production rate and inventories are rising in the short run because of the declining 'perceived process capability', which is the smoothed ratio of net to gross completion rate. Therefore, the simulated low-implementers are building up inventories and strive for higher production rates in order to compensate for higher rates of scrap elimination. Again, it is interesting to notice that this dynamics are generated entirely from different half-life times with no feedback from workers' commitment, skills or amount of labor force.

The result of another simulation experiment comparing the overall-high with the TQM-high implementers is outlined in Figure 12:

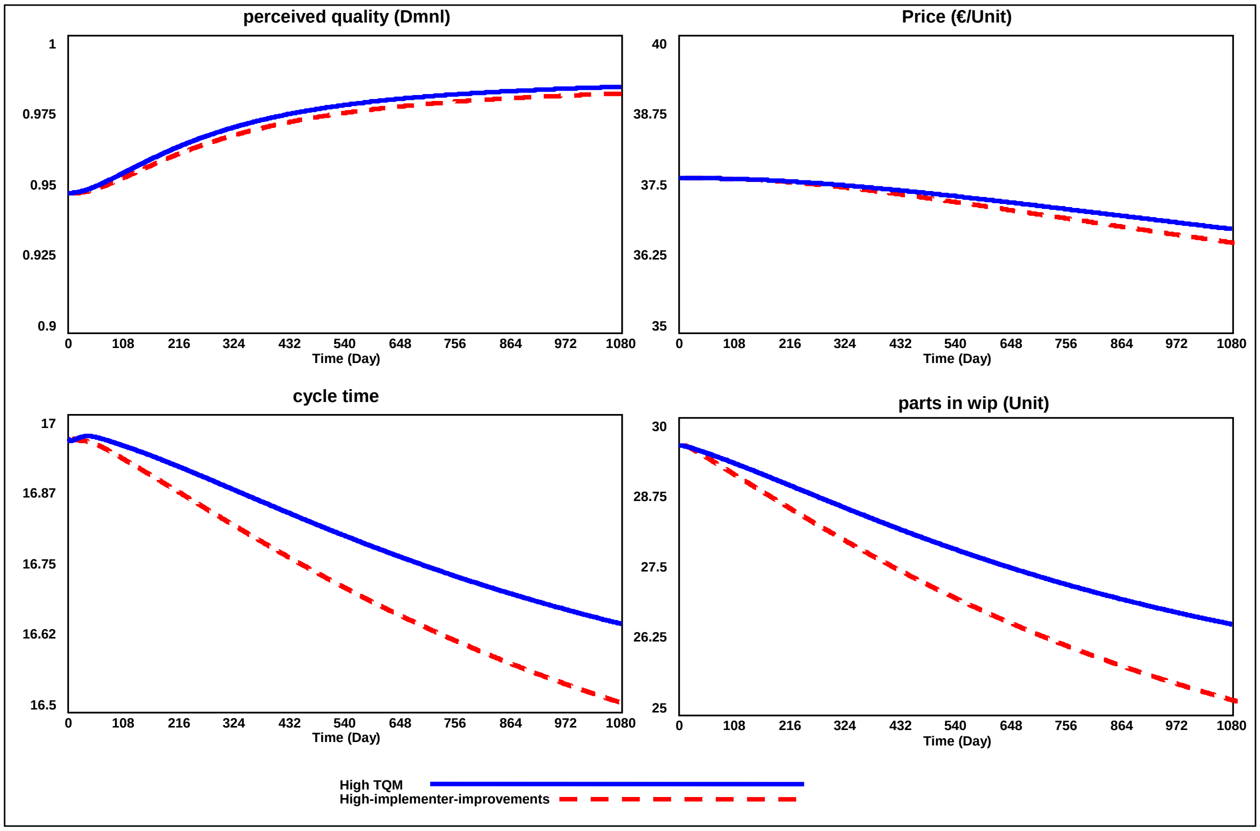

Figure 12: Comparison between TQM-high and overall-high implementers

The defect levels (state of internal and external TQM, processing time, etc., see Figure 7) are initialized equally to provide comparability. Beside that, the High-TQM simulation setting focuses on internal and external TQM as well as on TQC with little effort to the other programs. In contrast, the High-implementer-improvements setting possess an equally weighted improvement pattern with the same amount of effort to every program. The simulation runs show expected behavior in regard of the empirical investigations outlined in this article: even though the high TQM-high setting mainly emphasizes quality, it scarcely outperforms the over-all high implementing setting in 'perceived quality'. However, the over-all high implementing setting outperforms the TQM-high setting in other respects, like 'price', 'cycle time', and 'inventory'. Thus, the simulation runs confirm the statistical analyses.

Even though the interrelation between conducted improvement initiatives and learning is not established, the modeling attempts and simulation runs so far reveal noticeable results. Furthermore, they show accordance to the empirical data gathered by the author. Both, the statistical analyses and the simulation experiments show that 'balanced' program implementation patterns yield to better performance figures than patterns with a focus on a single program, like TQM. Another interesting finding is the existence of a worse-before-better-effect in the case of low-implementing plants, which is due to the different half-life times of the improvement programs (see Figure 11). In addition, the integration of empirical data and system dynamics modeling so far yields promising insights, which could not be gained with a solely conducted statistical analysis. Thus, the preliminary results provide a good basis for the intended extensions of the current model structure, which are highlighted in italics in Figure 5.

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Model listing

attrition=
labor force/attrition time
Units: Worker/Day

attrition time=
7200
Units: Day

average cost of machinery=
100
Units: €

average experience of new hires=
0.5
Units: Dmnl/Worker

average workers’ skill with process improvement=
workers' skill with improvement programs/labor force
Units: Dmnl/Worker

backlog= INTEG (
order dispatching-order fullfilment,
desired throughput time*order dispatching)
Units: Unit

change in perceived inventory turnover=
(cycle time-inventory turnover)/inventory turnover perception time
Units: Dmnl

change in perceived process yield=
(process yield-perceived process capability)/process yield perception time
Units: Dmnl/Day

competitive position costs=
1
Units: Dmnl

competitors price= INITIAL(
price*competitive position costs)
Units: €/Unit

completion rate=
min(production capacity,parts in wip/processing time)
Units: Unit/Day

cost of capital per unit=
(average cost of machinery+cycle time*interest*value of raw materials and wip
)/net completion rate
Units: €/Unit

costs per unit=
labor cost per unit+material costs per unit+cost of capital per unit
Units: €/Unit
cf. Milling 1974: 192

cycle time=
wip turnover+raw inventrory turnover
Units: Day

defective materials into inventory=
raw materials into inventory*"fraction of defective materials into inventory (suppliers' quality)"
Units: Unit/Day

defective materials into production process=
fraction of defective materials in raw inventory*materials into production process
Units: Unit/Day

defective parts completion=
completion rate*fraction of defective parts in wip
Units: Unit/Day

defective parts in wip= INTEG (
defective materials into production process+defects introduction-defective parts completion
,
materials into production process*(likelihood of defect introduction-likelihood of defect introduction
*fraction of defective materials in raw inventory+fraction of defective materials in raw inventory
)*processing time)
Units: Unit

defective raw materials in inventory= INTEG (
defective materials into inventory-defective materials into production process
,
"fraction of defective materials into inventory (suppliers' quality)"*desired raw materials inventory
)
Units: Unit

defects introduction=
likelihood of defect introduction*(materials into production process-defective materials into production process
)
Units: Unit/Day

demand=
normal demand*(effect of quality on demand+effect of price on demand+effect of time on demand
)/3
Units: Unit/Day

desired gross production rate=
MAX(0,desired production rate+desired wip adjustment)
Units: Unit/Day

desired labor=
desired gross production rate/perceived productivity of labor
Units: Worker

desired materials inventory adjustment=
(desired raw materials inventory-raw materials in inventory)/inventory adjustment time
Units: Unit/Day

desired production rate=
desired throughput/perceived process capability
Units: Unit/Day

desired raw materials coverage=
14
Units: Day

desired raw materials inventory=
desired gross production rate*desired raw materials coverage
Units: Unit

desired throughput=
backlog/desired throughput time
Units: Unit/Day

desired throughput time=
2
Units: Day

desired wip adjustment=
(desired work in process-parts in wip)/wip adjustment time
Units: Unit/Day

desired work in process=
desired production rate*processing time
Units: Unit

deterioration in defects detection=
(probability of defective parts detection-initial defects detection)*LN(2)
/erosion time defects detection
Units: Unit/(Worker*Day*Day)

deterioration in labor pdy=
(labor productivity-initial labor pdy)*LN(2)/erosion time labor pdy
Units: Unit/(Worker*Day*Day)

deterioration in suppliers' quality=
(initial fraction of defective materials into inventroy-"fraction of defective materials into inventory (suppliers' quality)"
)*LN(2)/erosion time suppliers quality
Units: Dmnl/Day

discovered defective parts=
probability of defective parts detection*defective parts completion
Units: Unit/Day

effect of price on demand= WITH LOOKUP (
perceived price ratio,
([(0,0)-(2,2)],(0,2),(1,1),(2,0)))
Units: Unit/Day

effect of quality on demand= WITH LOOKUP (
perceived quality,
([(0,0)-(1,1)],(0,0),(0.220183,0.0075188),(0.379205,0.0413534),(0.461774,
0.0789474),(0.53211,0.139098),(0.568807,0.184211),(0.599388,0.274436),(0.623853
,0.402256),(0.636086,0.515038),(0.657492,0.665414),(0.678899,0.789474),(0.697248
,0.845865),(0.718654,0.909774),(0.752294,0.943609),(0.801223,0.966165),(0.868502
,0.984962),(1,1)))
Units: Unit/Day

effect of time on demand= WITH LOOKUP (
"perceived on-time delivery",
([(0,0)-(2,2)],(0,1.33083),(0.489297,1.21805),(0.764526,1.14286),(1,1),(1.07034
,0.804511),(1.14985,0.488722),(1.29664,0.165414),(1.52294,0.0526316),(2,0)
))
Units: Unit/Day

erosion of machninery uptime=
(initial machinery downtime-fraction of machinery downtime)*LN(2)/erosion time machinery downtime
Units: Dmnl/Day

erosion time defects detection=
400
Units: Day

erosion time internal quality=
1080
Units: Day

erosion time labor pdy=
200
Units: Day

erosion time machinery downtime=
600
Units: Day

erosion time processing time=
1080
Units: Day

erosion time suppliers quality=
1080
Units: Day

expenses=
costs per unit*demand
Units: €/Day

FINAL TIME = 1080
Units: Day
The final time for the simulation.

financial resources= INTEG (
+revenues-expenses,
initial finances)
Units: €

fraction of defective materials in raw inventory=
defective raw materials in inventory/raw materials in inventory
Units: Dmnl

"fraction of defective materials into inventory (suppliers' quality)"= INTEG
(
(deterioration in suppliers' quality-improvements in suppliers' quality),
initial fraction of defective materials into inventroy)

Units: Dmnl

fraction of defective parts in wip=
defective parts in wip/parts in wip
Units: Dmnl

fraction of defective parts to customer=
ZIDZ(undiscovered defective parts completion,net completion rate)
Units: Dmnl

fraction of effort for defects detection=
0.2
Units: Dmnl/Day

fraction of effort for defects reduction=
0.2
Units: Dmnl/Day

fraction of effort for downtime reduction=
0.2
Units: Dmnl/Day

fraction of effort for labor pdy improvement=
0.2
Units: Dmnl/Day

fraction of effort for processing time=
0.2
Units: Dmnl/Day

fraction of effort for suppliers' quality=
0.2
Units: Dmnl/Day

fraction of machinery downtime= INTEG (
(-gain in machinery uptime+erosion of machninery uptime),
initial machinery downtime)
Units: Dmnl

gain in machinery uptime=
LN(2)*(fraction of machinery downtime-minimum machinery downtime)/"half-life time in machinery downtime reduction"
*fraction of effort for downtime reduction
*workers' improvement effort
Units: Dmnl/Day

"half-life defects detection"=
72
Units: Day
The half-life for defects detection is comparatively low. in
accordance to (Schneiderman 1988) I assume 2.4 months (2.4*30=72)

"half-life labor pdy improvement"=
660
Units: Day
This value is an assumption

"half-life suppliers' quality improvement (optimal)"=
660
Units: Day
The observed half-life time of improvements spanning over
mutiple organizations is 22 months (Schneiderman 1988)
(22*30=660)

"half-life time defects reduction (optimal)"=
312
Units: Day
The observed half-life time of manufacturing cycle time is 10.4
months (Schneiderman 1988) (10.4*30=312)

"half-life time in machinery downtime reduction"=
135
Units: Day
The observed half-life time to reduce machinery downtime is 4.5
months (Schneiderman 1988) (4.5*30=135)

"half-life time process improvement (optimal)"=
507
Units: Day
The observed half-life time of manufacturing cycle time is 16.9
months (Schneiderman 1988) (16.9*30=507)

hiring=
MAX(labor gap/time to hire,0)+labor replacements
Units: Worker/Day

improvements in defect introduction=
(likelihood of defect introduction-minimum likelihood of defects introduction
)*LN(2)/"half-life time defects reduction (optimal)"
*fraction of effort for defects reduction*workers' improvement effort
Units: Dmnl/Day

improvements in defects detection=
(maximum defects detection-probability of defective parts detection)*LN(2)
*workers' improvement effort*fraction of effort for defects detection
/"half-life defects detection"
Units: Dmnl/Day

improvements in labor pdy=
(maximum labor pdy-labor productivity)*LN(2)*workers' improvement effort*fraction of effort for labor pdy
improvement
/"half-life labor pdy improvement"
Units: Unit/(Worker*Day*Day)

improvements in processing time=
(processing time-minimum processing time)*LN(2)/"half-life time process improvement (optimal)"
*workers' improvement effort
*fraction of effort for processing time
Units: Dmnl/Day

improvements in suppliers' quality=
("fraction of defective materials into inventory (suppliers' quality)"-minimum fraction of defective materials from
supplier
)/"half-life suppliers' quality improvement (optimal)"*LN(2)*workers' improvement effort

*fraction of effort for suppliers' quality
Units: Dmnl/Day

increase in experience=
on the job learning*labor force*workers commitment
Units: Dmnl/Day

increase in experience from new hiring=
hiring*average experience of new hires
Units: Dmnl/Day

increase in likelihood of defect introduction=
(initial likelihood of defect introduction-likelihood of defect introduction
)*LN(2)/erosion time internal quality
Units: Dmnl/Day

increase in processing time=
(initital processing time-processing time)*LN(2)/erosion time processing time
Units: Day/Day

inital pdy=
10
Units: Unit/(Worker*Day)

initial competitive position time=
1
Units: Dmnl

initial defects detection=
0.9
Units: Dmnl

initial finances=
1e+006
Units: €

initial fraction of defective materials into inventroy=
0.2
Units: Dmnl

initial labor pdy=
10
Units: Dmnl

initial likelihood of defect introduction=
0.2
Units: Dmnl

initial machinery downtime=
0.1
Units: Dmnl

INITIAL TIME = 0
Units: Day
The initial time for the simulation.

initital processing time=

2
Units: Day

interest=
0.1
Units: Dmnl

inventory adjustment time=
14
Units: Day

inventory turnover= INTEG (
change in perceived inventory turnover,
cycle time)
Units: Day

inventory turnover perception time=
7
Units: Day

labor cost per unit=
"wages (daybased)"*labor force/net completion rate
Units: €/Unit
This variable gives the labor costs per unit. (cf. Milling 1974:
192)

labor force= INTEG (
+hiring-attrition-layoffs,
desired labor)
Units: Worker

labor gap=
desired labor-labor force
Units: Worker

labor productivity= INTEG (
(-deterioration in labor pdy+improvements in labor pdy),
initial labor pdy)
Units: Unit/(Worker*Day)

labor replacements=
SMOOTH(attrition,time to perceive labor attrition)
Units: Worker/Day

layoffs=
MAX((-1)*labor gap ,0)/time to layoff
Units: Worker/Day

likelihood of defect introduction= INTEG (
(+increase in likelihood of defect introduction-improvements in defect introduction
),
initial likelihood of defect introduction)
Units: Dmnl

machinery capacity=
10000
Units: Unit/Day

margin=
0.15
Units: Dmnl

market perception time=
60
Units: Day

material costs per unit=
10
Units: €/Unit

materials into production process=
min(desired gross production rate,raw materials in inventory/setup time)
Units: Unit/Day

maximum defects detection=
1
Units: Dmnl

maximum labor pdy=
25
Units: Unit/(Worker*Day)

minimum fraction of defective materials from supplier=
0
Units: Dmnl

minimum likelihood of defects introduction=
0
Units: Dmnl

minimum machinery downtime=
0
Units: Dmnl

minimum processing time=
1
Units: Day

net completion rate=
completion rate-discovered defective parts
Units: Unit/Day

normal demand=
10
Units: Unit/Day

on the job learning=
7e-005
Units: Dmnl/Worker

order dispatching=
demand
Units: Unit/Day

order fullfilment=
net completion rate
Units: Unit/Day

orders=
MAX(0, desired gross production rate+desired materials inventory adjustment
)
Units: Unit/Day

parts in wip= INTEG (
+materials into production process-completion rate,
desired work in process)
Units: Unit

"perceived on-time delivery"=
SMOOTHi(backlog/net completion rate /desired throughput time,market perception time
,initial competitive position time)
Units: Day

perceived price ratio=
SMOOTHi(ZIDZ(price,competitors price), market perception time,1/competitive position costs
)
Units: €/Unit

perceived process capability= INTEG (
change in perceived process yield,
1-probability of defective parts detection*(likelihood of defect introduction
-likelihood of defect introduction*"fraction of defective materials into inventory (suppliers' quality)"
+"fraction of defective materials into inventory (suppliers' quality)"))
Units: Dmnl

perceived productivity of labor=
SMOOTHi(labor productivity, perception time labor productiovity,inital pdy
)
Units: Unit/(Day*Worker)

perceived quality=
SMOOTHi((1-fraction of defective parts to customer),market perception time
,1-(1-probability of defective parts detection)*(likelihood of defect introduction
-likelihood of defect introduction*"fraction of defective materials into inventory (suppliers' quality)"
+"fraction of defective materials into inventory (suppliers' quality)") / (
1-(likelihood of defect introduction-likelihood of defect introduction*"fraction of defective materials into inventory
(suppliers' quality)"
+"fraction of defective materials into inventory (suppliers' quality)")*probability of defective parts detection
))
Units: Dmnl
This variable needs an initial in order to avoid simultaneous
initial value equations. the initial is 1-a*(1-b)/(1-ba) with: a
= (likelihood of defect introduction-likelihood of defect
introduction*"fraction of defective materials into inventory
(suppliers' quality)"+"fraction of defective materials into
inventory (suppliers' quality)") b = probability of defective
parts detection

perception time labor productiovity=
30
Units: Day

price=
SMOOTH(costs per unit*(1+margin), price change time)
Units: €/Unit

price change time=
30
Units: Day

probability of defective parts detection= INTEG (
(-deterioration in defects detection+improvements in defects detection),
initial defects detection)
Units: Unit/(Worker*Day)

process yield=
ZIDZ(net completion rate, completion rate)
Units: Dmnl

process yield perception time=
7
Units: Day

processing time= INTEG (
(increase in processing time-improvements in processing time),
initital processing time)
Units: Day

production capacity=
min(machinery capacity,labor force*labor productivity)
Units: Unit/Day

raw inventrory turnover=
ZIDZ(raw materials in inventory, materials into production process)
Units: Day

raw materials in inventory= INTEG (
+raw materials into inventory-materials into production process,
desired raw materials inventory)
Units: Unit

raw materials into inventory=
DELAY1(orders,time to deliver)
Units: Unit/Day

revenues=
demand*price
Units: €/Day

SAVEPER =
TIME STEP
Units: Day
The frequency with which output is stored.

setup time=
1
Units: Day

skill loss=
(attrition+layoffs)*average workers' skill with process improvement
Units: Dmnl/Day

TIME STEP = 0.125
Units: Day
The time step for the simulation.

time to deliver=
7
Units: Day

time to hire=
30
Units: Day

time to layoff=
1080
Units: Day

time to perceive labor attrition=
14
Units: Day

undiscovered defective parts completion=
defective parts completion-discovered defective parts
Units: Unit/Day

value of raw materials and wip=
2
Units: €/Unit

"wages (daybased)"=
2500/30
Units: €/(Worker*Day)

wip adjustment time=
7
Units: Day

wip turnover=
ZIDZ(parts in wip, net completion rate)
Units: Day

workers commitment=
1
Units: Dmnl

workers' improvement effort=
average workers' skill with process improvement*workers commitment
Units: Dmnl

workers' skill with improvement programs= INTEG (
+increase in experience+increase in experience from new hiring-skill loss,
(hiring*average experience of new hires+on the job learning*labor force*workers commitment
)*attrition time)
Units: Dmnl