Demand Planning Model - V1

Overview, Design, Concepts and Details (ODD)

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The model description follows the overview, design concepts, details (ODD) protocol (Grimm et al., 2006; Grimm et al., 2010), which is common for agent-based model documentation (Hauke, Lorscheid, & Meyer, 2017). The conceptual model is implemented in AnyLogic 8.1.0, a multimethod simulation modeling tool (AnyLogic, 2017). The implemented model (file name: Demand Planning Model - V1) can be downloaded in the *open abm* model library: https://www.openabm.org/.

1 Purpose

The model was designed to contain a simplified representation of a demand planning process with different outcomes of forecast accuracy. Purpose of the model is to show how individual cognition (sensitivities) of different actors in the demand planning process and the way they interact affects forecast accuracy. In this respect, the model takes a specific perspective, which results from the following context of a case study company in the semiconductor industry.

In the demand planning process of the case company more and more steps have been automated and are now supported by IT systems. Still, the IT systems may not include all aspects for successful demand planning. Human decision makers are considered to be far better in identifying chances and mitigating risks in the volatile planning environment. For example, they can anticipate possible regulatory changes for the automotive industry and can factor in what this means for the demand forecast. Nevertheless, human decision makers are not perfect and their cognitive properties may also affect the planning performance negatively, for example by overreacting or acting on biased or only partial information (Bassamboo, Cui, & Moreno, 2015; Brueggen, Grabner, & Sedatole, 2014). For this reason, it is considered as crucial by the company to better understand human behavior and how the behavioral traits and resulting interactions of individual actors influence successful demand planning (Achter et al., in prep.).

The model presented can be understood as part of a larger project. In the context of the situation described above we address a specific aspect considered as highly relevant for subsequent processes and planning accuracy in the company. The actors in the planning process perceive different relevant aspects of the environment. This makes information sharing between the specialized actors important. However, their perception can potentially be biased. The question is under which conditions one can actually expect an improvement of planning accuracy. Does information sharing always result in improvements?

Another example of a practically relevant question is how to design or adapt the process to improve either planning accuracy or efficiency. Purpose of the model is to provide a conceptual computational testbed for the investigation of such types of questions, based on a careful analysis of the interactions between the actors in the planning process. Overall, we aim to investigate effects of individual cognition, the process structure and team interactions on forecast accuracy.

2 Entities, states, variables and scales

The model includes four types of individuals, a sales planner (SP), marketing planner (MP), supply chain planner (SCP) and team leader (TL).[1] Model parameter distinguished in global and individual variables of agents are summarized in Table 1.

SP, MP, SCP and TL have distinct cognitive skills to sense future customer demand. These skills are reflected with the individual variables of *sensitivity*. The higher the *sensitivity*, the more accurate is an agent`s perception of *orders* for a future period. Further, individual parameters characterize the behavior

[1] The labels of the agents are representatives for important actors in the planning process. These labels might differ in practice. Also, other agents might matter in the process. We assume these four are the most important for our illustration of the computational testbed.

of the SCP and TL. The parameter *deviation* represents a decision rule of the SCP to communicate with the SP and MP. The TL has a certain degree of trust in the work of the SCP, whereas the magnitude is reflected with the individual parameter *trust*. High values of trust means high trust in the skills of the SCP.

In each time step any individual can accomplish a single action. A period of planning corresponds to one week. A *period* comprises a variable number of time steps. The simulated *planning horizon* is set to 26 periods.[2] Space is not represented. In the default setting 26 *periods* of planning are simulated, whereas in each *period* a plan is developed for future periods within the *planning horizon*.

Customer demand is represented by the global variable *orders* that reflect customer demand (an order pattern) over 52 periods. This order pattern represents a specific demand scenario of a simulation run and is a model input. The *control horizon* reflects a decision relevant time horizon that is in particular relevant for decisions of the SCP and TL.

The output is measured by the variable forecast accuracy that is calculated for three different planning horizons: *long-term forecast accuracy* (26 periods), *medium-term forecast accuracy* (10 periods), and *short-term forecast accuracy* (1 period). Another output variable counts the number of *plan revisions.* The number of plan revisions is limited by the parameter *max revisions* to a maximum of 10 plan changes per period in the default setting. Further the output is measured with the variable *team interactions* that counts direct communication between the SCP and TL as well as communication between SCP, SP and MP.

Table 1: Description of model parameters, values and ranges.

Global Variables	**Description**	**Default value**
Orders	Indicates customer orders of past and future periods	Empirical data of customer demand for 52 periods
Scale	Normalizes the perception of agents to the scale of orders	100
Periods	Number of planning periods of a simulation run	26
Planning_horizon	The planning horizon	26
Control_horizon	The control horizon that is relevant for the SCP and TL	10
Max_revisions	The number of plan revisions within a planning period	10
Long-term forecast_accuracy	Planning accuracy within the planning horizon	Varies as the model iterates
Medium-term forecast_accuracy	Planning accuracy within the control horizon	Varies as the model iterates
Short-term forecast_accuracy	Planning accuracy for the upcoming period	Varies as the model iterates
Plan_revisions	The number of plan revisions within a period	Varies as the model iterates
Team_interactions	The number of interactions among agents within a period	Varies as the model iterates
Individual Variables	**Description**	**Default Value**
SP_sensitivity	Cognitive capability of the SP to sense orders	0.7
MP_Sensitivity	Cognitive capability of the MP to sense orders	0.1
SCP_Sensitivity	Cognitive capability of the SCP to sense orders	0.3
TL_Sensitivity	Cognitive capability of the TL to sense orders	1.0
Deviation	Decision threshold of the SCP to communicate	100
Trust	Trust in the skills of the SCP by the TL	0.5

3 Process overview and scheduling

The planning process is depicted in Figure 1. Aim of planning is the development of an unconstrained demand plan.[3] In the first step the SP and MP sense future orders for each period within the planning horizon. These planners report their sales and marketing forecast via a planning tool.

In the second step, the SCP starts planning by retrieving sales and marketing report from the planning system and decides whether to recalculate or to maintain a plan from a previous period.[4] If the SCP decides to maintain the plan, then the SCP only adds the last period to the plan and hands the plan to

[2] Other companies or divisions may setup plans with other planning horizons, e.g., 52 weeks.
[3] The development of an unconstrained demand plan is the initial subtask in the entire supply chain planning process of the case study company. We denominate this subtask also as forecasting.
[4] In the very first period is no actual plan available, so the planner recognizes a new planning situation.

the TL. Otherwise the SCP has the option to recalculate the plan based on information retrieved from the planning system or to initialize a direct communication with SP and MP to obtain further information.

When the SCP has collected sufficient information about sales and marketing situation, then the planner uses this information to calculate the demand plan. Afterwards the SCP hands the plan to the team leader, who can either instruct the SCP to revise the plan or accepts the plan. If the planner is supposed to revise the plan, the planner again decides about the revision of the plan.[5] A period ends, when the SCP has saved the plan. Output of the process is an unconstrained demand plan that comprises 26 weeks of future demand expected by the demand planning team. The unconstrained demand plan is the basis to determine stock levels and a production program in subsequent process steps that are actually not reflected in the model for reasons of simplification.

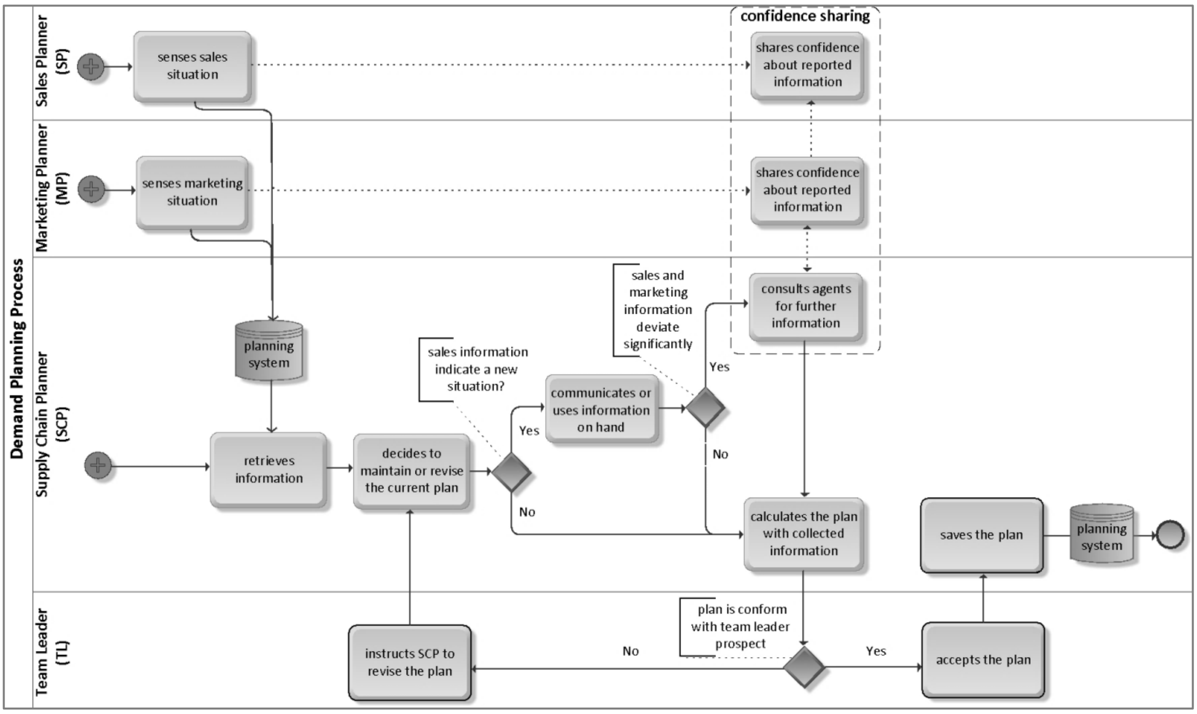

Figure 1: BPMN diagram of the demand planning process.

4 Design concepts

4.1 Basic principle

This basic model is a simplified representation of the demand planning process of a semiconductor company. The model is designed from a distributed cognition perspective, which focusses on the information flow and processing among humans and artifacts (Hutchins, 1995; Nilsson et al., 2012). The model is further grounded in the theory on organizational routines that relates organizational behavior on a macro level to interactions of individuals on a micro level (Felin & Foss, 2009; Salvato & Rerup, 2010). The modelling approach follows for two reasons the "keep it simple, stupid" (KISS) principle (Axelrod, 1997; Sun et al., 2016). First, the model should easily adapted to planning processes of other companies beyond the case used for modelling. Second, the model is regarded as first module that is projected to be extended, to incorporate in next modelling steps stock planning, capacity restrictions, and the development of a production program.

[5] This iterative loop is interrupted by the team leader after 10 iterations, set by the parameter *max revisions*. Then the plan is saved as provided by the planner in the 10th loop.

4.2 Emergence

The demand plan emerges from the cognitive traits and behavior of the agents, thus this is an emergent result of the planning process. The submodel used to represent communication between SCP and SP as well as MP can result in outcomes that are hard to predict. Nevertheless, also simpler submodels would result in demand plans that are non-predictable due to the cognitive traits of agents that are stochastic modelled.

4.3 Adaption

In particular the SCP behaves adaptive to different planning situations. The adaptive behavior is based on simple empirical rules, which were observed in a participating observer study (shadowing of different SCP) in the case company. At first SCP behavior is contingent to the actual sales situation. In cases, when actual reported sales exceed the demand plan the SCP revises the plan. Further, the communication behavior of the SCP is contingent on the conformity of sales and marketing reports.

4.4 Objectives

Objective of the SCP is to determine an accurate demand plan. Therefore, the SCP always revises a plan if actual sales information indicate a new situation. Further, the SCP tolerates only limited discrepancies of reported sales and marketing information. This is described with the decision parameter *deviation.* The lower this threshold the more accurate is the planning approach of the SCP, and the more probable is that the SCP communicates with the SP and MP to obtain more detailed information. Although, communication can result in outcomes that are even more contradictory in view to the conformity of sales and marketing information. Moreover, the TL follows the objective to avoid planning errors. Target value of the TL agent is its estimate of accumulated demand for future periods within the control horizon. The demand plan developed by the SCP is assessed by the TL on this estimate in association with the trust in the skills of the SCP. Trust in a SCP is assumed to be dependent on experience and associated with skills of a SCP.

4.5 Learning

Learning agents that change their adaptive traits over time are not reflected in the model. Nevertheless, dynamic settings of the sensitivities of agents could reflect simple linear learning by increasing the parameter values for selected agents within a simulation run. Hence, the individual cognitive skills of agents would improve over time.

4.6 Prediction

The decision of the SCP to maintain or revise a plan as well as the decision to communicate with the SP and MP implies tacit predictions of the SCP. The first decision implies the prediction of the SCP that the current plan may does not match to future demand any longer. To predict such a change of environmental conditions the SCP applies the actual sales report as indicator. Further, the SCP implicit predicts that planning with reported sales and marketing information may result in poor demand plans if reported demand significantly differs. This influences the decision of the SCP to initiate communication with the SP and MP.

4.7 Sensing

Sensing by agents is important in the model. SP, MP, SCP and TL are able to sense the external environment, in the dimension of future orders (customer demand). The mechanisms, how agents sense future orders are modelled explicitly. It is assumed that agents may sense demand biased, which is determined by their sensitivity. Basically, we assume that higher sensitivity corresponds to the proximity to an information source. E.g., the SP has better information about a customer compared to a

MP who has more knowledge about specific product characteristics. Also other cases are possible, e.g., experienced MP and inexperienced SP. An exception is that the SCP senses information retrieved from the planning system (sales and marketing report) unbiased. Also, shared sensing and decision making of the SCP and SP as well as SCP and MP is reflected by the weighted confidence sharing model that is used as submodel (Bahrami et al., 2010).

4.8 Interaction

The model includes direct as well indirect interaction. Indirect interaction occurs while agents communicate information via the planning system. The forecast reports of the SP and MP are retrieved by the SCP via a planning system and are an initial signal for the SCP to start planning of a new period. While planning the SCP can decide to initiate direct communication with the SP and MP, which is represented by the weighted confidence sharing model. This interaction affects the calculation of the plan by the SCP. Communication between SCP and TL is modelled as direct interaction, whereas the result affect the next action of the SCP to either save the plan or to revise the plan (again).

4.9 Stochasticity

Stochasticity is used to model cognitive limited agents. Sensing of future orders is biased by normal distributions that are defined with the sensitivity parameters. As sensed information also affect decisions of the SCP and TL the decision behavior of the agents is consequently partly stochastic. Following the assumption that decisions of the agents are not rigid as empirically observed.

4.10 Collectives

The model includes two predefined collectives (dyads) of SCP and SP as well as SCP and MP. During direct communication these dyads make collective decisions about future demand. This is modelled with a shared sensitivity that is constituted of the individual cognitive properties of the agents and defined by the weighted confidence sharing model (Bahrami et al., 2010). Another collective is the interaction of the SCP and TL.

4.11 Observations

Data collected from the ABM are in particular used to analyze, how different settings of cognitive skills (sensitivities) affect forecast accuracy e.g. to analyze if cognitive skills of the SCP matter in terms of forecast accuracy. Furthermore, the number of team interactions and plan revisions can contribute to determine process designs with favored outcomes, e.g., process designs that result in demand plans with robust forecast accuracy in different scenarios of customer behavior.

5 Initialization

The initial state of the model is described by the default values of the parameters (see again Table 1). The environmental scenario of customer demand is reflected with an order pattern that is used as model input (see Figure 2). The seed values for each simulation run are varied. This induced stochasticity results, even in a constant environmental condition and parameter setting, in changing planning behavior of agents. In the very first period is no plan from a previous period available, thus the SCP has to set up a new plan.

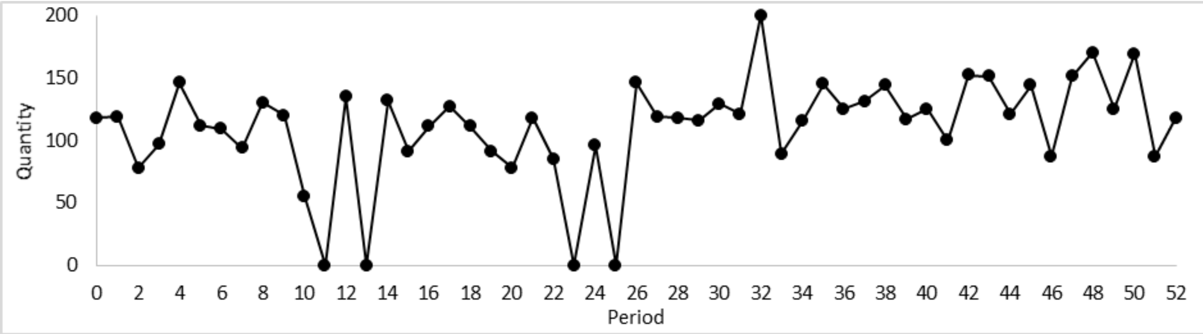

Figure 2: Empirical order pattern of product 1 normalized to a range of 0 to 200.

6 Model input

Empirical order pattern of customers are used as model input. The order pattern comprises 52 periods including the quantity of billings per period (see Table 2). The model dynamics are driven by this time series of customer demand. Due to confidentiality reasons the pattern used is normalized to demand quantity that ranges between 0 and 200. However, also other ranges can be simulated by adjusting the parameter *scale* to the median of the demand quantity range.

Table 2: Time series of orders for product 1.

Period	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
Quantity	118	119	78	97	146	112	109	94	130	120	55	0	135	0	132	91	111	127	111	91	78	118	85	0	96	0
Period	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
Quantity	119	118	116	129	121	200	89	116	145	125	131	144	117	125	100	152	151	121	144	87	151	170	125	169	87	118

7 Submodels

In this section the incorporated submodels are elaborated. The order follows possible procedure calls within a planning period. Also different submodels have been tested, e.g. other communication models as the weighted confidence model. The introduction of other submodels, e.g., different probability distributions with skewness, provide an opportunity to analyze further settings such as risk averse or risk seeking agents.

7.1 Demand sensing by agents

The agents forecast demand by sensing each future period separately. The perception of agents is biased by normal distributions, whereas the standard deviation determines the cognitive bias of an agent.[6] A sensitivity of 1.0 reflects non biased perception, whereas lower values increase the probability of an agent to sense demand biased. The standard deviation of an agent (A) is determined as follows.

$$\sigma_{\mathrm{A}} = \mathrm{Scale} - \mathrm{Scale} * \mathrm{Sensitivty}_{\mathrm{A}}$$

7.2 Decision of the Supply Chain Planner to revise a plan

The SCP compares the demand plan of the previous period and the actual sales forecast. Thereby, the SCP focusses on periods within the control horizon. If the SCP recognizes that the actual sales forecast extends the demand plan within the control horizon for at least one period, then the agent decides to revise the demand plan, as defined by the following formula.

[6] The normal distributions are truncated to the lower bound (0), as forecasting negative values of demand does empirically not occur.

$$\mathrm{SalesReport_P} > \mathrm{DemandPlan_P} \quad \forall\ p \in [1, ch]$$

7.3 Decision of the Supply Chain Planner to communicate

The SCP compares reported sales and marketing information for each period. If the SCP detects for any period a discrepancy greater than the parameter deviation, then the SCP decides to communicate with the SP as well as with the MP. This decision rule is expressed by the following term.

$$\mathrm{Deviation} < \mathrm{SalesReport_P} - \mathrm{MarketingReport_P} \quad \forall\ p \in [1, ph]$$

7.4 Communication

Given the importance of decentralized information processing by agents and their confidence in shared information, a crucial element is the weighted confidence sharing model. This also allows for non-trivial results of communication, i.e. information quality goes down. The model is tested as most accurate for collective perceptual decision making tasks (Bahrami et al., 2010). Given this concept, during direct communication of two agents their perceptions are shared. The shared sensitivity of a dyad is calculated with the individual sensitivities of agent (A) and agent (B) as follows.

$$\mathrm{Sensitivity_{dyad}} = \frac{\mathrm{Sensitivty_A} + \mathrm{Sensitivity_B}}{\sqrt{2}}$$

7.5 Plan calculation by the Supply Chain Planner

The SCP calculates a demand plan on collected information about sales and marketing demand, either retrieved from the planning system or obtained due to communication. The plan is calculated for each period of the planning horizon. The period to be planned (*p*) is indicated by an incremental index. Increasing uncertainty in remote future periods is accounted by a weighting of sales and marketing information according to the following formula.

$$\mathrm{DemandPlan_P} = \mathrm{SalesDemand_P} * \left(1 - \frac{p}{ph}\right) + \mathrm{MarketingDemand_P} * \frac{p}{ph} \quad \forall\ p \in [1, ph]$$

7.6 Team Leader decision

The TL checks the developed plan by the SCP to avoid planning errors. The TL senses orders within the control horizon to make an aggregated estimate about future demand. The estimate and the parameter *trust* influence the decision of the team leader. The TL accepts the plan, if the following term is true.

$$\sum_{p=1}^{ch} \text{Estimate of } \mathrm{TL_P} * (1 + \mathrm{Trust}) > \sum_{p=1}^{ch} \mathrm{DemandPlan_p} > \sum_{p=1}^{ch} \text{Estimate of } \mathrm{TL_P} * (1 - \mathrm{Trust})$$

7.7 Measures of interactions, plan changes and forecast accuracy

We measure *team interactions* by counting the interactions between SCP and SP/MP (counted as a single interaction as the SCP communicates with both, if the planner decides to communicate) as well as SCP and TL. The number of *plan revisions* is measured by counting how often the SCP revises a plan within a period. We use the Symmetric Mean Average Percentage Error (SMAPE) to calculate the forecast errors. The measure is defined as average of absolute errors divided by the sum of the actual and forecasted value over (p) periods. The value A_t indicates the quantity of orders for a period (t) and F_t the forecasted value, therewith *forecast accuracy* is calculated as follows.

$$\text{Forecast accuracy (\%)} = 100\% - \frac{100\ \%}{p} \sum_{t=1}^{p} \frac{|A_t - F_t|}{(|A_t| + |F_t|)}$$

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