Can simulation help to understand the impact of management practices on retail productivity?

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•In Nottingham we investigate the impact of management practice from an Operational Research (OR) point of view.

•OR applies advanced analytical methods to help making better (informed) decisions.

•One method used in OR for system analysis is simulation which we have decided to use for this project.

•There are different types of simulation. The one we are using is the same that is used in these computer games (SIMS & SIMCITY). It’s called Agent-Based Simulation. More later …

•What we are developing is a kind of strategic simulation game that helps us to learn about the impact of management practice on retail store productivity.

•This can be used on the one hand to investigate different scenarios but on the other hand also to communicate ideas.

Goals of our simulation study

- Develop a simulation model that helps to understand and predict the impact of different management practices on retail store productivity
- Focus on individual departments within department store
- Incorporating variables from different levels of analysis
- Simulation study supported by case studies
- Using a new technology: Agent-Based Simulation

> "Agent-Based Simulation is used to study how micro level processes affect macro level outcome; macro behaviour is not simulated, it emerges from the micro decisions of the individual agents."

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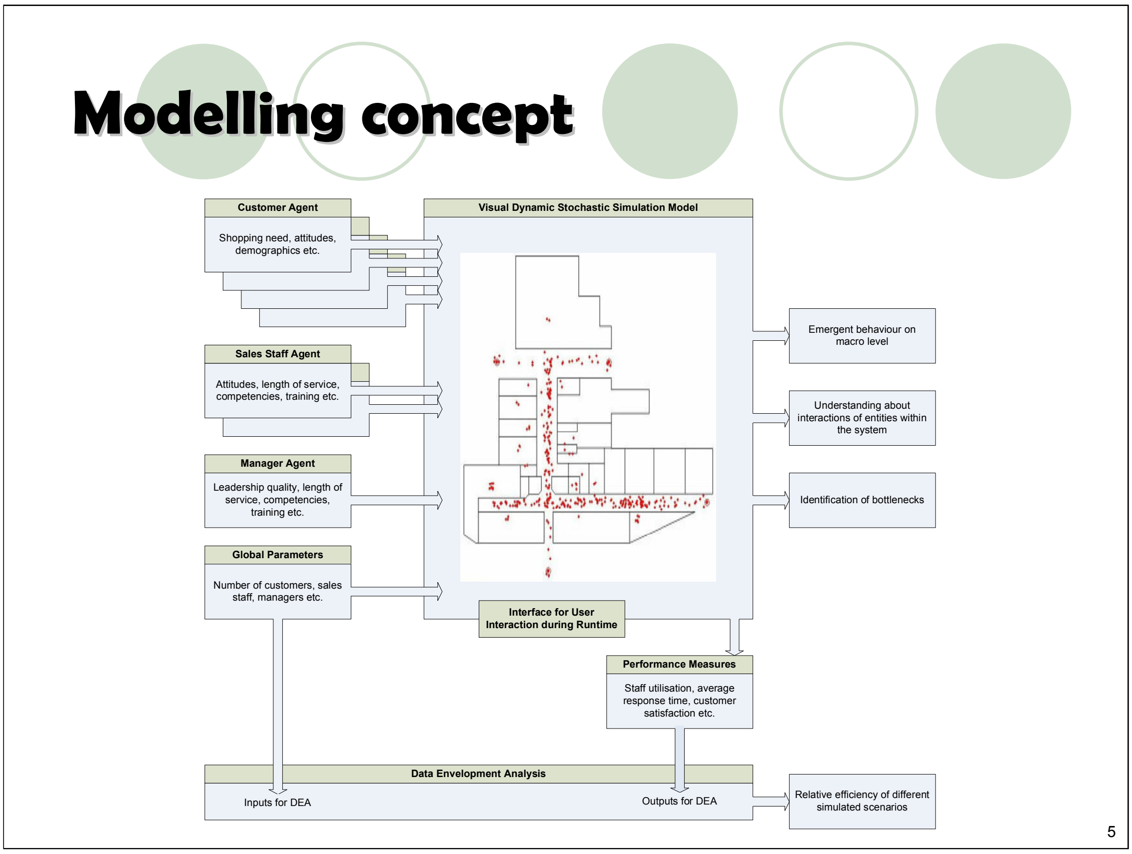
•The simulation model will provide insight into the operation of the system over a defined period of time. It allows to monitor the system state at any point in time during the simulation run, a capability that many other OR methods cannot provide.

•An important point to keep in mind: The more accurate the system model (more real data, less assumptions) the higher the probability that the predictions (performance values as well as representation of system operation) will relate to the performance of the real system.

•The predicted performance is not to be understood as an absolute indication of system performance (as a simulation model is only a restricted copy of the real world and therefore not suitable to make absolute predictions). Instead, it should be used as an indicator to allow the comparison of the results received from different experiments. Example: benefit of having 3 rather than 2 tills; comparing cost vs. customer drop out rate.

•Different level of analysis: This means during the simulation run we monitor and later analyse the behaviour of individual actors (e.g. utilisation), work teams (e.g. co-operation level), and the overall department (e.g. reputation growth/loss).



•Once we had decided which method to use we captured our thoughts and ideas about the department store simulator in a conceptual model.

•A conceptual model shows the inputs, components, and outputs of a simulation model without defining them in great detail.

Where do we use collected data?

- Define the research question
- Define model components
- Building the model
- Validate and tweak model
- Interpret and explain our simulation results
- Understand the operation of a department store to be able to give qualified recommendations

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•Data required for defining the research questions (defining scenarios, what is interested to investigate): Understanding about store operations and the behaviour of the partners/managers (case study).

•Data required to define model components (state charts and required parameters that allow to differentiate between actors): Observation of partners to identify their main activities (case study).

•Data required for building the model (numerical estimates of delays and probabilities): Estimations of task durations, queue lengths, queuing times, footfall data, conversion rates (estimates from DMs/SMs, database printouts)

•In order to get meaningful results we need footfall data (hourly, per department) and real conversion rates. We have staffing information (rota samples) and transaction analyses (hourly sales) for all departments that were part of the case studies.

•Data required for validation and model tweaking (e.g. sensitivity analysis, test with historical data): Validation will be done using sales data and queue length estimates. We can use them to adjust our other numerical estimates to achieve similar sales data and queue lengths with our simulation model by recreating historical scenarios. A sensitivity analysis will tell us which input data (when changed slightly) have a big impact on the simulation model output and therefore their data sources need to be as accurate as possible (using collected data rather then estimates, if possible).

•Data required to interpret and explain our simulation results: We need to have a contextual understanding to interpret and explain the simulation results (case study).

•The same is true to allow us to give qualified recommendations.

Definition of research questions (1/2)

- Management Practice: Training
  - Staff at different training levels
  - Product oriented vs. customer oriented

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•Currently we focus on HR management practices. It has been shown in studies on other sectors (e.g. manufacturing □ Birdi et al., 2006) that HR management practices have a significantly bigger impact on performance than operational management practices.

•The chosen HR management practices build on each other: it is difficult to initiate empowerment without having well trained staff that feel confident when making decisions. Therefore, we will build one simulation model and gradually enhance it to support investigating the impact of the different practices one after the other.

•Management Practice - Training (1): Number of normal staff vs. number of experts (this is what we focus on at the moment); individual vs. cross training (modelled by impact on individual (partner motivation, customer satisfaction), impact on department (customer satisfaction, reputation, word of mouth), cost penalty, reduced service times).

•Management Practice - Training (2): What kind of training to focus on when the budget is limited (modelled by cost penalty, reduced service times, customer satisfaction; needs customer stereotype definitions to define different challenges for partners). Scenarios: even distribution, uneven distribution, optimal training levels vs. cost

Definition of research questions (2/2)

- Management Practice: Empowerment
  - Refunds
  - Break times
  - Remain when other staff assist
- Other Aspects
  - Customer population

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•Management Practice - Empowerment (1): Example would be the requirement of an SM to authorise refunds (modelled by time penalty to wait for SM, number of wrong decision might be higher with more empowerment as SMs have more experience), partner motivation). Scenarios: only manager, everyone, some staff, one central till, everyone for most items (e.g. 75% of time - equivalent of £50)

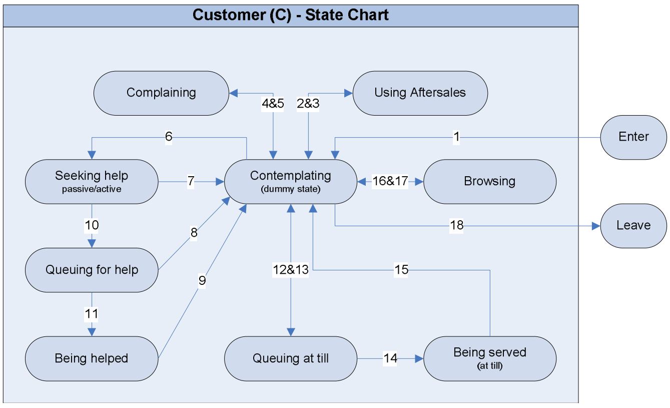
•Management Practice - Empowerment (2): Taking breaks. Scenarios: fixed, variable, self-scheduled when department is not busy (staff on break cannot sell)

•Management Practice - Empowerment (3): Decision made by staff member to stay with customer and enhance knowledge (so next time he/she can give advice without asking for support) vs. departmental guideline). Scenarios: always, never, when department is not busy (staff cannot sell whilst staying with customer but acquire product training)

•Other aspects (1):Modelling different arrival rates and different types of customers. Scenarios: random, stereotypes, actual footfall, evolving (i.e. satisfaction ratings carry over)

•Some of these aspects require long simulation runs before they show an impact, in particular those that are related to learning/evolution.

Definition of model components



NB: Arrows leaving 'Observe' carry the smaller numbers, incoming ones the larger numbers.

What activities do Cs spend 80% of their time on?
Which ones can be interrupted?
What is different between different stereotypes?
What triggers state changes immediately, after timeout, if signal event occurs, if change event occurs, at a specific rate?

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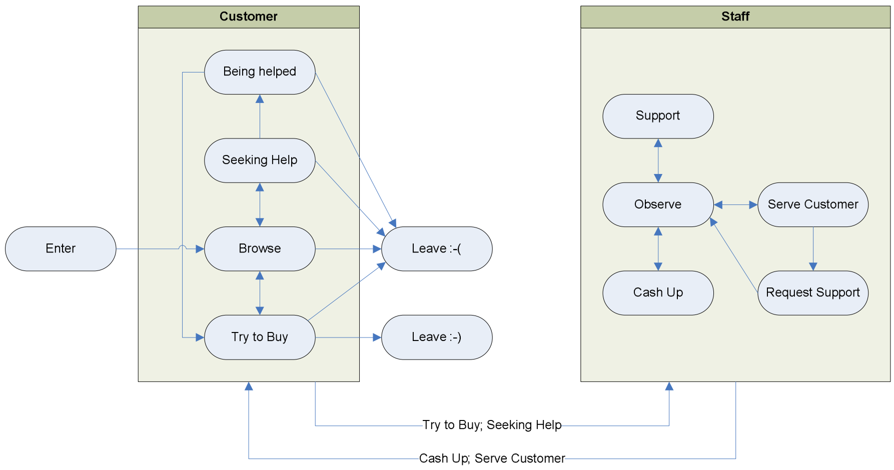
•The art of modelling is simplification and abstraction. A model is always a restricted copy of the real world and you have to try and identify the most important components of a system or in our case the most important activities of an actor (e.g. for customer: browsing, seeking help, complaining, queuing) and triggers to move from one state to another (e.g. time delay, requests from other actors).

•Example: Customer state chart

Our first attempt …

- Modelling the effect of staff training



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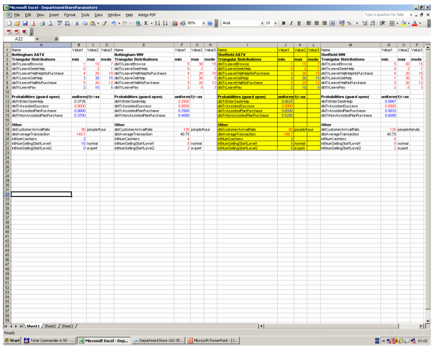
•We model three different levels of staff: dedicated cashiers, normal selling partners with general knowledge, expert selling partners with expert knowledge

•There is a probability (e.g. 10%) that a normal selling partner cannot give sufficient advice and has to call in an expert. If no expert is available the customer has to wait. If the customer has to wait too long he might decide to leave (like service time the patience is based on a distribution)

•We can vary the number and role of staff members. The question is: What would be the best composition?

•Currently we haven’t added costs but later there will be a cost penalty per cash point (large) and also for experts (small) as they require extra training.

Model input: Scenario 1



Name	Value1	Value2	Value3
Sheffield A&TV			
Triangular Distributions	**min**	**max**	**mode**
dblTrLeaveBrowse	1	15	7
dblTrLeaveSeekHelp	0	2	1
dblTrLeaveWaitHelpNoPurchase	4	20	10
dblTrLeaveGetHelp	3	30	15
dblTrLeaveWaitNoPurchase	5	20	12
dblTrLeavePay	2	10	5
Probabilities (guard open)	**uniform(1)<=xx**		
dblTrEnterSeekHelp	0.6625		
dblTrAssistedSuccess	0.9000		
dblTrAssistedPlanPurchase	0.6500		
dblTrNonAssistedPlanPurchase	0.5250		
Other			
dblCustomerArrivalRate	80	people/hour	
dblAverageTransaction	149.7		
intNumCashiers	2		
intNumSellingStaffLevel1	5	normal	
intNumSellingStaffLevel2	5	expert	

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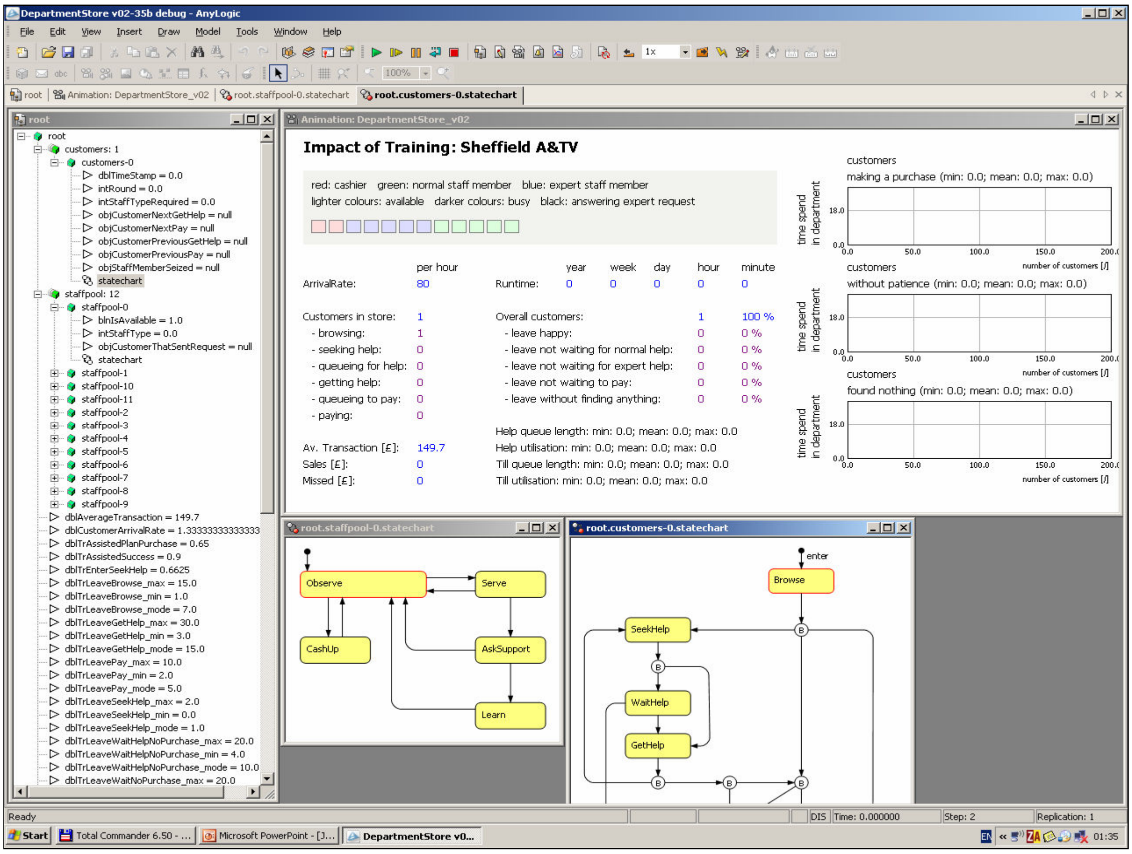
•This is the Excel front-end for the model where you can set up the experiment conditions (all department specific data is stored here and can be easily protected e.g. by hiding and password protecting sensitive data rows, there are no data stored directly in the simulation model).

•For this example we have chosen the Audio & TV department.

•Currently most of the data are guesses or expert estimates.

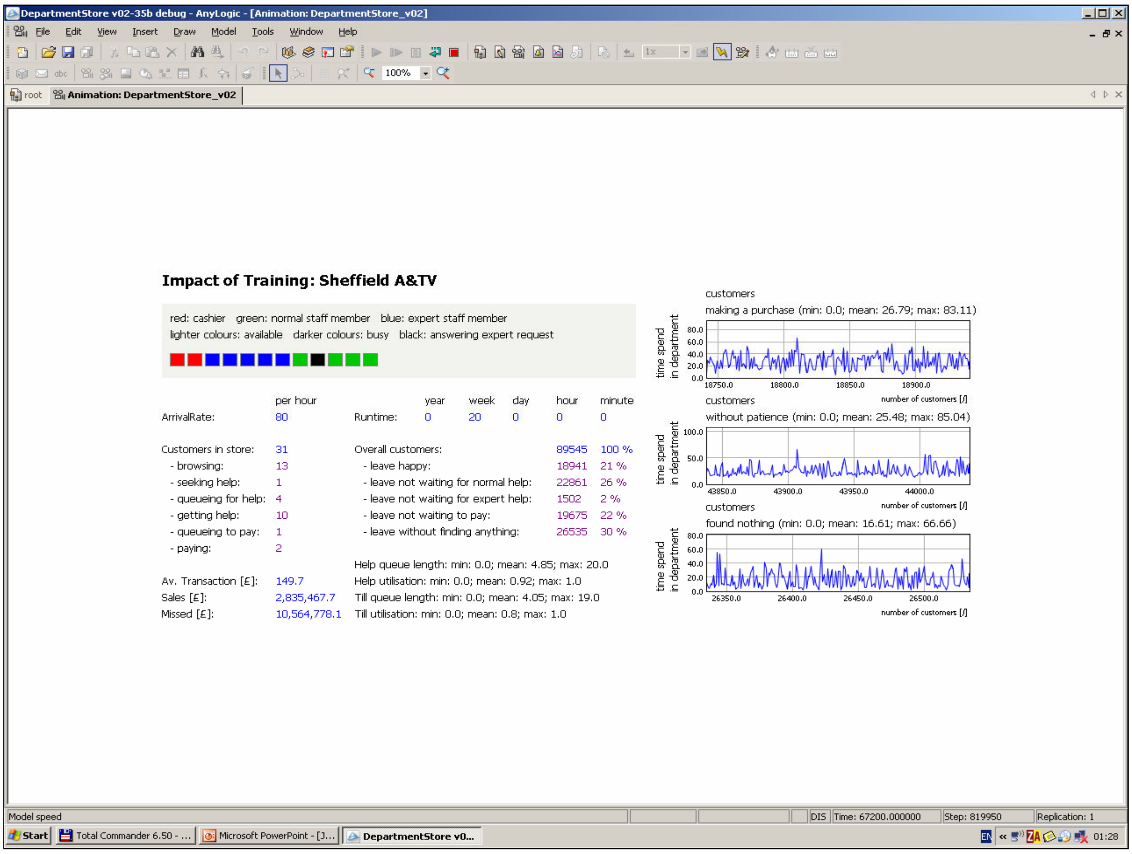
•In the top we have defined delays using triangular distributions (e.g. service time at the till); in the middle we have conversion rates defined as probabilities (e.g. likelihood that someone makes a purchase after he/she has been helped by a partner) and in the bottom we have the global model parameters (footfall, average transaction value and split of staff roles).

•For our first experiment we use the following parameters: footfall: 80 customers/hour; staff setup: 2 cashiers, 5 normal staff and 5 experts.



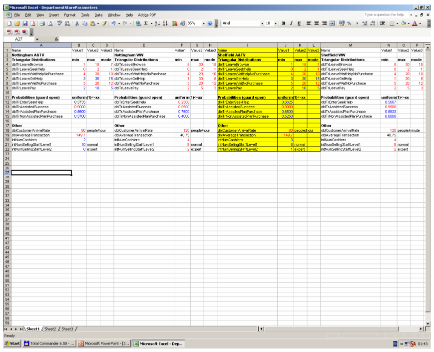
•The model is implemented in AnyLogic (multi paradigm simulation software) and the screenshot shows the model just after the start of the experiment.

•On the left you can see that each staff member and customer is individually represented with different parameter values. You can see from the statistics window that our first customer has arrives. From the state chart displayed below the statistics screen you can see that this customer is in browsing state while the partner (here for example one of the cashiers) is in observe state.



•The final result shows us that only 21% of our customers leave happy (26% did not want to wait for normal help and 2% for expert help; 22% did not want to wait at the till). You can also see the queue lengths (at average 5 customers are queuing for advice and 4 at the till) and utilisation of selling partners and cashiers. On the right you can see how much time each customer spent in the department.

Model input: Scenario 2



Name	Value1	Value2	Value3
Sheffield A&TV			
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dblTrAssistedPlanPurchase	0.6500		
dblTrNonAssistedPlanPurchase	0.5250		
Other			
dblCustomerArrivalRate	80	people/hour	
dblAverageTransaction	149.7		
intNumCashiers	3		
intNumSellingStaffLevel1	8	normal	
intNumSellingStaffLevel2	1	expert	

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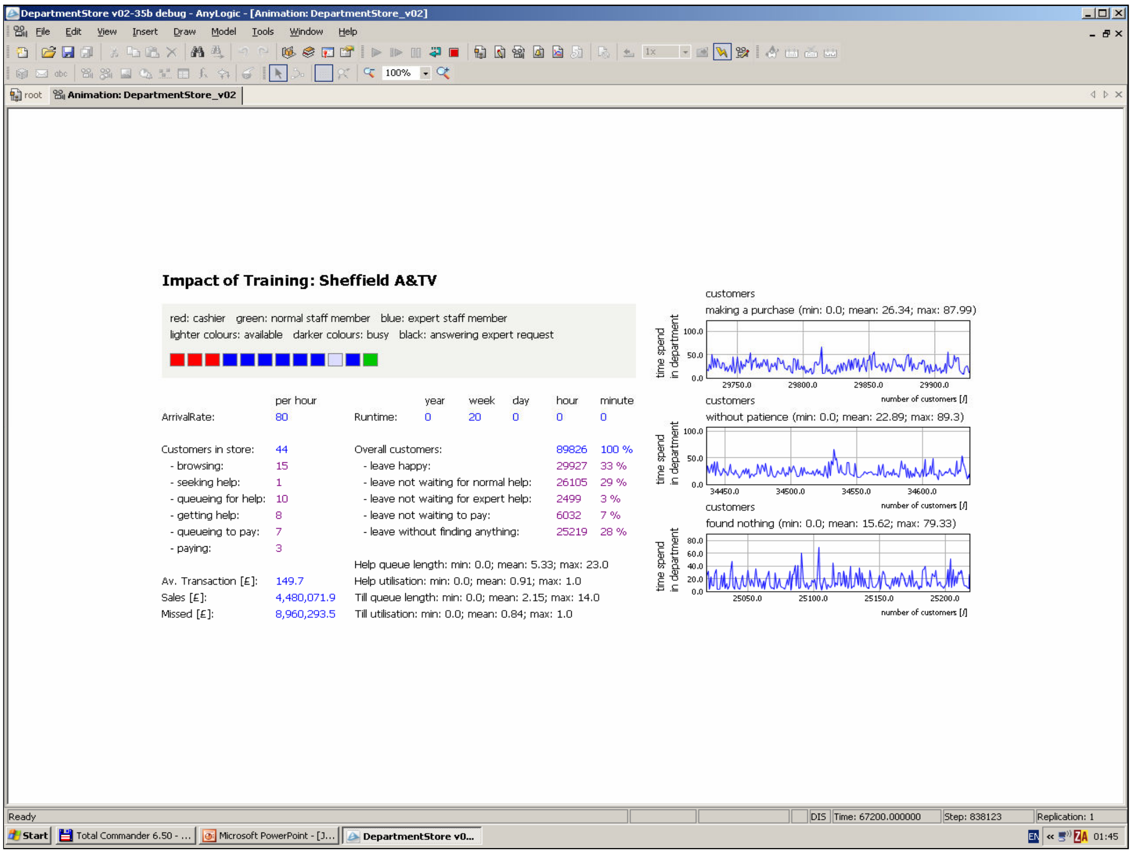
•For our second experiment we use the following parameters: 80 customers/hour, 3 cashiers, 8 normal staff and 1 expert. We still have the same number of staff but we have responded to the results from the previous experiment by having more tills open to reduce the number of customers leaving before paying (last stage → they might have received some help beforehand and therefore have cost us time/money; we don't want to loose them in the last moment, rather we would accept to loose some people waiting for help).

•Lets see if our theory is correct …



•Results from the first experiment: Only 21% of our customers leave happy (26% did not want to wait for normal help and 2% for expert help; 22% did not want to wait at the till) and at average 5 customers were queuing for advice and 4 at the till.

•Results from the second experiment: We reduced the number of customers leaving because they did not want to wait at the till significantly by 15%. Our number of customers leaving happy has also gone up significantly by 12%. Despite the fact that we lost most of our exerts (4 out of 5) the number of customers leaving because they did not want to wait for an expert has only risen by 1% which is acceptable. The number of customers leaving because they did not want to wait for normal help has risen by 3% which is acceptable looking at all the benefits. Of course the overall rate of 29% is not acceptable, so for the next experiments we should gradually add more normal selling staff and see when we reach an acceptable level of customers leaving because they don't want to wait for help.

•By making these small adjustments in staffing we boosted our sales from 2.8 million to 4.5 million. Of course the model is very simple and uses mainly data based on assumption rather than on measures and is neither verified nor validated but it already shows us a trend and we can have a think if this trend in principle makes sense.

•Once we've extended our model replaced guesses with staff estimates (e.g. % of customers requiring secondary help) or measured data (e.g. footfall, conversion rates) our predictions will become more accurate and reliable.

Questions?

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