Worker Performance Modeling in Manufacturing Systems Simulation: Proposal for an Agent-Based Approach

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Abstract

Discrete event simulation is generally recognized as a valuable aid to the strategic and tactical decision making that is required in the evaluation stage of the manufacturing systems design and redesign processes. It is common practice to represent workers within these simulation models as simple resources, often using deterministic performance values derived from time studies. This form of representing the factory worker ignores the potentially large effect that human performance variation can have on system performance and it particularly affects the predictive capability of simulation models with a high proportion of manual tasks. The intentions of the chapter are twofold: firstly, to raise awareness of the importance of considering human performance variation in such simulation models and secondly, to present some conceptual ideas for developing a worker agent for representing worker performance in manufacturing systems simulation models.

1 Introduction

Manufacturing systems are most often highly complex constructs and their behavior is of a dynamic and stochastic nature. They consist of extensive interactions between people, information, materials and machines. Systems like assembly lines may look quite simple because their tasks are mainly done in a sequential order. In reality, these systems are quite complex constructs due to natural variation in processing times which makes them non-deterministic, and breakdowns of various types. These breakdowns can be machine failures, but in systems like manual assembly lines where humans play a key role they can also be unusually long task completion times or the unavailability of workers.

When it comes to the design or redesign of manufacturing systems it is common to use a methodological approach. Discrete Event Simulation (DES) is generally recognized as a valuable aid to the strategic and tactical decision making that is required in the evaluation stage of the design process. Figure 1 depicts the way in which DES integrates into the manufacturing system design process. A major advantage of simulation models compared to the analytical ones which are also in use, is their ability to model random events based on standard and non-standard distributions and to predict the complex interactions between these events. This allows the system designer to obtain a system wide view of the effect of local changes to the performance of the overall system and enables him or her to predict system performance, to compare alternative system designs and to determine the effect of alternative policies on system performance.

Amongst other things, DES models are used to determine the amount of machines, buffers and operators that are needed to produce a certain target output. Companies that have groups which specialize in studying multi-million dollar systems using DES include Honda, Ford, General Motors, Harley-Davidson and Renault (Baudin, 2002). The simulation experts within these groups have a high degree of responsibility to ensure the accuracy of the results. Inaccuracy can prove very costly, as it may lead to poor system performance and failure to meet the production demand.

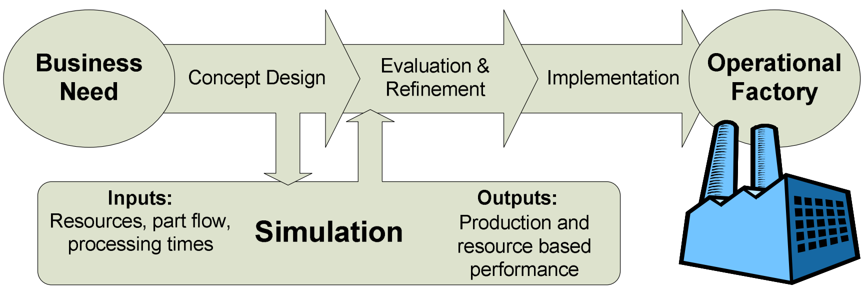

Figure 1: Steps in manufacturing systems design

Due to the complexity of the real world a system model can only be a restricted copy of a real system. Therefore, abstraction and simplification have to be used in order to cope with this complexity. Abstraction comprises or concentrates in itself the essential qualities or behaviors of a thing, but not necessarily in the same form or detail as in the original while simplification entails stripping away unimportant details and assuming simpler relationships (Shannon, 1975).

It is commonly observed that a gap exists between the performance predictions of a manufacturing system simulation model and the performance of the real system. As a consequence of abstraction and simplification, system models tend to model the real world too optimistically compared to real systems. Another common observation is that performance predictions of systems involving a high proportion of manual tasks are notably less accurate than those of highly automated systems. This is attributed to the way in which the human element is represented within the system simulation model. It is common practice within DES models to represent workers as simple resources, often using deterministic performance values derived from time and motion studies. This is an extreme simplification as the work measurement literature indicates clearly that workers' task performance varies. This variation occurs between different workers carrying out the same task and moreover for the same worker when repeating a task (see for example Dudley, 1968). It has also been shown that workers' task performance varies as a consequence of its dependence on past events and the current state of the system. The current approach of representing workers within DES models ignores the potentially large effect that Human Performance Variation (HPV) can have on the system performance of the labor intensive manufacturing system.

This chapter has been written with two objectives in mind: firstly, to raise awareness of the importance of considering HPV in human oriented DES models and secondly, to offer some conceptual ideas for developing a more sophisticated representation of direct workers (people, dedicated to predominately manual routines) in DES models. The chapter is therefore split into two main parts. The first part reports on research that has been conducted to address the first objective. It describes a field experiment carried out to quantify direct worker performance variations in automotive manual assembly lines and test the sensitivity of simulation models towards these variations. It then discusses the results and the limitations of the approach that has been chosen to represent these variations. The second part consists of a collection of ideas which is intended to contribute towards achieving the second objective in the near future. A literature review is provided to identify design opportunities that allow a more advanced representation of worker variability and behavior in manufacturing systems simulation models. These opportunities are derived from the systems engineering and the social science literature, where human performance and behavior modeling is already used for many different purposes in many different ways. An agent based approach is identified as the most suitable way forward and concepts for a worker agent and its integration into manufacturing system simulation models are developed. The chapter concludes by discussing the problems of implementing the proposed concepts and identifying possibilities for future work.

2 The Need for Non-Deterministic Models of Worker Performance

A common means of representing the performance of direct workers within manufacturing system simulation models is to use so called standard times. These are the times required by an average skilled worker, working at a normal pace, to perform a specific task using a prescribed method, allowing time for personal needs, fatigue, and delay. They are mean values derived either from direct work measurements through means of time studies or from indirect work measurements through means of synthetic timing. Using mean values and ignoring the natural variation in these task completion times represents a significant simplification that can have a high impact on the simulation model runtime behavior and consequently on the accuracy of the performance predictions of the simulation model. On the other hand it might be that due to the long runtime of the simulation models (usually several months are simulated) the variation equilibrates and therefore the simplification is legitimate. This section describes some research that has been carried out to investigate this issue by means of a sensitivity analysis.

2.1 Sensitivity Analysis Using Empirical Frequency Distributions

Firstly, a long term data collection exercise was conducted to quantify the performance variation of direct workers in a typical automotive manual engine assembly flow line (Siebers, 2004). The line that has been observed is divided into ten different work zones. In each work zone the work is performed by a team of six to twelve workers. The workers rotate by the hour in their subsequent zone which means that each individual works on all the tasks in his or her section. Data about the activity times (basically the time that an individual is working on a particular engine) were collected at ten different workstations over a period of three months using an automated data collection method. The collected data were also used to analyze the break taking behavior of the workers. Figure 2 shows a time series plot of the collected data points for one particular work station over an eight hour shift. Due to the rotation mentioned earlier each hour slice represents the activity times of a different worker. The diagram shows clearly that there are differences in activity times when a worker repeats a task and also between different workers. Furthermore it can be seen that the actual breaks are significantly longer than the planned breaks.

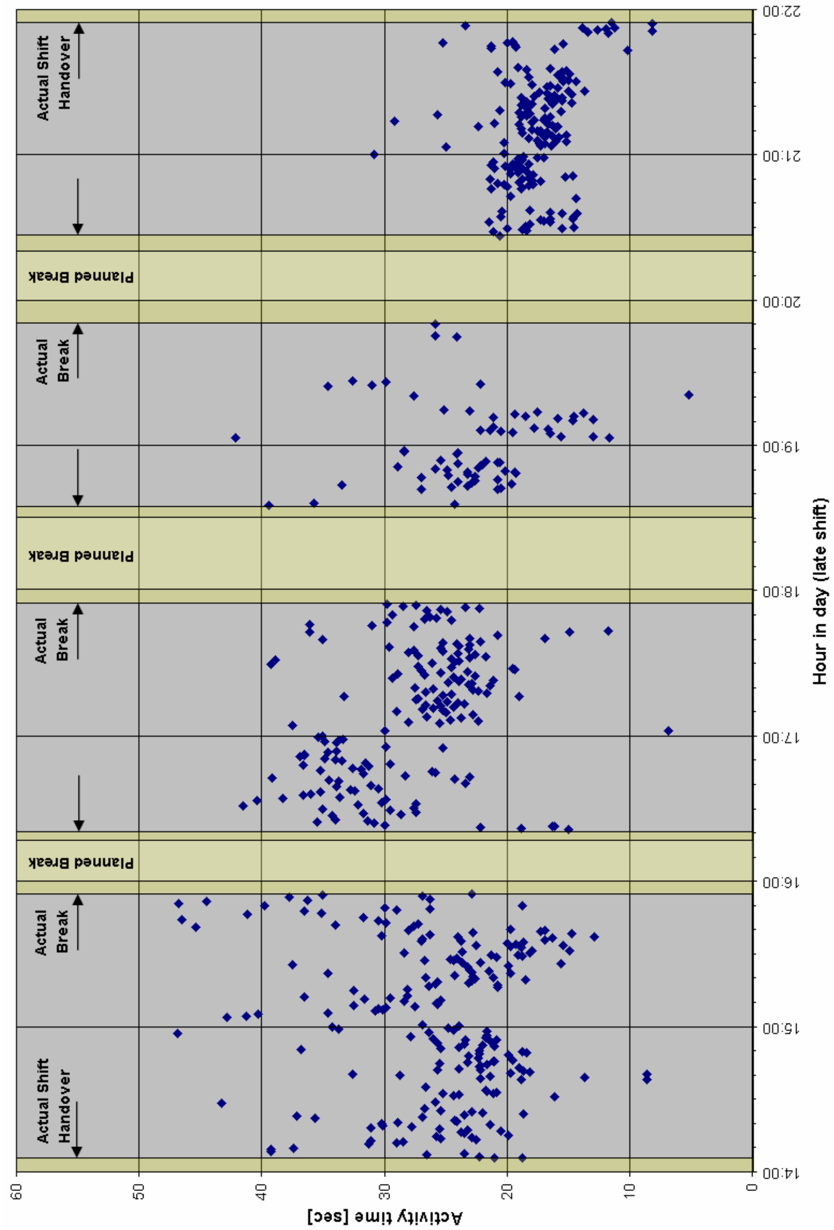

Figure 2: Activity time variations for a manual workstation during an eight hour shift

The collected data were then transformed into empirical frequency distributions representing activity time variations and break taking behavior. This format supports the integration of the collected data into DES models. By looking at the resulting frequency distributions it was found that the scattering of activity times is dependent of the nature of the task and that there is no generic pattern for manual tasks. For the frequency distributions representing break taking behavior it was shown that the scattering of the break start and break duration does not depend on the break length. The average disruption due to leaving the workstation early and coming back late was the same for all breaks.

In order to enable a sensitivity analysis, the designed empirical frequency distributions were inserted into simulation models of existing engine assembly lines (each with approximately 100 workstations) to represent the performance variation of the direct workers at the individual workstations. Through designed experiments, the effect that this form of HPV modeling has on the behavior of the simulation models was investigated.

The results from these experiments showed that the representation of HPV can have a significant impact on the behavior of the system simulation models. The impact depends basically on the type of variation to be represented as well as on the system to be modeled. While the impact of activity time variation is system dependent (which is the same in the real world) and depends amongst other things on the buffer sizes (bigger impact on systems with smaller buffer sizes), the impact of break taking behavior is always present.

As a result of these investigations, system designers employing simulation as a decision support tool should now be aware of the consequences that ignoring variation in worker performance may have on the validity of their system analysis.

2.2 Limitations of the Empirical Frequency Distribution Approach

Despite the fact that using empirical frequency distributions is a step forward compared to current standards in the simulation community it has two major drawbacks. The first one is that the distributions are context specific, that is to say form and magnitude of HPV is amongst others a function of task, workforce composition, environment and location. No generic distribution shape could be identified to describe HPV. Therefore, using the distributions in locations other than their origin will reduce their validity. The second drawback which is even more severe is that the distributions on their own are not capable of expressing interdependencies between events and do not consider the state of the system as values are chosen at random.

Conversely, research has shown that the activity time of workers is dependent on past events and the current state of the system. Schultz et al. (1998) for example, have presented evidence that worker behavior differs, depending on the size and status of the buffers surrounding them and with whom the worker is teamed. Doerr et al. (1996) found that workers speed up when they are the cause of idle time, even in the absence of management pressure. De Souza & Zhao (1997) argue that a complete and effective representation of dynamic behavior would require a composite representation of knowledge in various forms.

It has been proposed that the use of a combination of rules and distributions for representing the dynamic behavior of workers would be a step forward. The rules would allow a guided choice of stochastic values based on the system status, profile and state of the individual worker and the work group he or she is working in. This would preserve the stochastic nature of the individual component while considering interdependencies with other components of the system.

Ideally, workers would be modeled as autonomous and proactive entities, constantly monitoring their environment, reasoning and reacting to internal and external stimuli. This would account for the fact that in human oriented systems compared to nonhuman ones an additional level of feedback is occurring. People notice what is going on around them and adjust their behavior accordingly, a phenomenon also known as second-order emergence (Gilbert & Troitzsch, 1999).

3 A Literature Review on Models of Human Performance

Over the past few decades, tools and techniques for modeling and predicting human performance in complex systems have evolved and matured. Pew & Mavor (1998) state that models and techniques are emerging within the systems engineering and social science domains, that clearly indicate that some valid modeling of operator performance is possible. Table 1 provides a classification of human performance modeling approaches. Details about the elements can be found in Elkind et al. (1990) for the Systems Engineering approaches and in Gilbert & Troitzsch (1999) for the Social Science approaches.

Simulation is a new way of examining social and economic processes by studying the emergence of complex behavior from relative simple activities (Gilbert & Troitzsch, 1999). The study of complex systems is a new field of science related to complexity theory. It examines how parts of a system lead to the collective behaviors of the system, and how the system interacts with its environment. It cuts across all traditional disciplines of science, as well as engineering, management, and medicine and is about understanding indirect effects that are not obviously related to their causes (Bar-Yam, 1997). Complex Adaptive Systems (CAS) are a specific category of complex systems that change their behavior in response to their environment (Bar-Yam, 1997). They are denoted by the following three characteristics: evolution, aggregate behavior and anticipation (Holland, 1992; Trisoglio, 1995). Here, evolution refers to the adaptation of systems to changing environments, aggregate behavior refers to the emergence of overall system behavior from the behavior of its components and anticipation refers to the expectations the intelligent agents involved have regarding future outcomes. Since CAS adapt to their environment, the effect of environmental change cannot be understood by considering its direct impact alone. Therefore, the indirect effects also have to be considered due to the adaptive response.

Systems Engineering	References
Bio mechanical models	e.g. Kroemer et al. (1988)
Information sensing and processing models	e.g. Harris et al. (1986)
Knowledge based/cognitive approach	e.g. Sasou et al. (1996)
Optimal control theory models	e.g. McCoy & Levary (2000)
Anthropometric models	e.g. Kroemer et al. (1988)
Task network models	e.g. Laughery (1998)
Workload prediction models	e.g. Hendy & Farrell (1997)
Situational awareness models	e.g. Corker (1999)
Human reliability models	e.g. Sebok et al. (1997)
Micro models	e.g. Spencer (1987)
Integrated models	e.g. Bunting & Belyavin (1999)

Social Science	References
Artificial society modeling (some of the main forms)	e.g. Epstein & Axtell (1996)
- Microsimulation	e.g. Orcutt (1986)
- Cellular automata	e.g. Gaylord & D'Andria (1998)
- Production systems	e.g. Ye & Carley (1995)
- Multi-agent modeling	e.g. Weiss (1999)
- Learning and adaptive models	e.g. Axelrod (1987)
Descriptive human performance modeling	e.g. Schultz et al. (1999)
Emergency simulation	e.g. Olenick & Carpenter (2003)

Table 1: Human performance modeling in Systems Engineering and Social Science

Organizations, which are basically groups of people that are working together in order to attain common goals, can be characterized as CAS composed of intelligent, task-oriented, boundedly-rational, socially-situated agents. These agents are faced with an environment that has the potential for change (Carley & Prietula, 1994). Computational Organization Theory (COT) is concerned with building new concepts, theories, and knowledge about organizing and organization in the abstract, to develop tools and procedures for the validation and analysis of computational organizational models, and to reflect these computational abstractions back to actual organizational practice through both tools and knowledge (Carley & Gasser, 1999). One of the most commonly used techniques to model CAS is multi-agent based modeling (Skvoretz, 2003) where the organization is composed of a number of intelligent agents. Unlike traditional multi-agent models, COT models draw on and have implemented into them empirical knowledge from Organization Science about how the human organizations operate and about basic principles for organizing (Carley & Gasser, 1999).

Another way of describing a human oriented manufacturing system is to see it as an organization in which groups of people work together to attain common goals. These groups include for example machine operators or assembly line workers. It seems that COT can also provide a promising paradigm for modeling the behavior of factory workers. The use of multi-agent based models is also supported by Henk (1993) who states that multi-agent based models show promise as models of organizations, since they are based on the idea that most of the work in human organizations is done based on intelligence, communication, cooperation, and massive parallel processing.

4 Proposition for an Agent-Based Approach to Worker Performance Modeling

As already discussed above, workers within manufacturing system simulation models would ideally be modeled as autonomous and proactive entities, constantly monitoring their environment, reasoning and reacting to internal and external stimuli. Multi-agent based modeling has been identified as a promising way forward. In the following section we develop some ideas of what such a system could look like. The motivation is not to present a working Multi-Agent System (MAS) but to present some considerations and thoughts to support the development of such a system.

A top-down approach has been taken. It begins by describing some conceptual ideas for a multi-agent based Worker Performance Modeling (WPM) tool and its integration into the DES modeling environment of the manufacturing system. This is followed by a brief review of existing agent architectures. Different models and frameworks from Occupational Psychology and Organizational Behavior research are then examined that could help to decide about the factors and state descriptors to be considered inside the agent architecture. Finally, a worker agent framework is presented that in the author's view could be used to develop some worker agents.

4.1 Ideas for a Multi-Agent Based Worker Performance Modeling Tool

The task of developing a multi-agent based modeling tool that is capable of representing workers within DES models is very challenging. Therefore a three step development process is proposed that gradually increases in complexity and still produces useful tools at the end of each development step.

Figure 3 represents the deliverable at the end of the first step which is a generic theory building tool. No manufacturing system process data is required. The tool can be seen as an artificial white room, i.e. a simulation of a laboratory as it is used for data gathering under controlled conditions. The output of the tool would support the development of lookup tables, functions and distributions that describe system independent variations in state and performance of a workforce at individual and group level. These outputs can be used to represent worker and workgroup performance in new or existing manufacturing simulation models.

Figure 3: Tool development after step 1; Generic theory building approach

Figure 4 represents the deliverable at the end of the second step which consists of a task based approach. In comparison to the first tool, the output would be system related. The tool would require basic process and layout setup data as well as task definitions for the individual agents. Therefore the output of the tool would support the development of lookup tables, functions and distributions tailored for a specific manufacturing system.

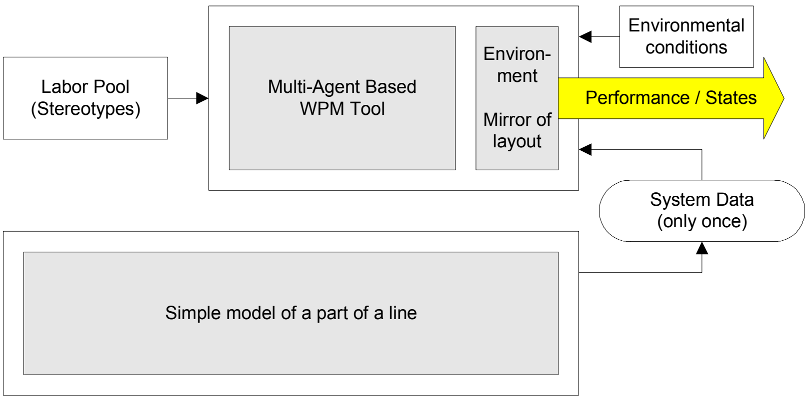

Figure 4: Tool development after step 2; Task based approach

Figure 5 represents the deliverable at the end of the third and final step which consists of a situation based or integrated approach. Here the MAS takes over the representation of the workers within the manufacturing system simulation model. The state of the agents is updated whenever the state of the system changes and feedback of agent state changes is given to the manufacturing system simulation model. Once the simulation is finished, the data from the multi-agent based tool can be stored in a knowledge base to allow comparison of the behavior of agents in different scenarios later. This might support the development of new behavioral rules to implement in the tool.

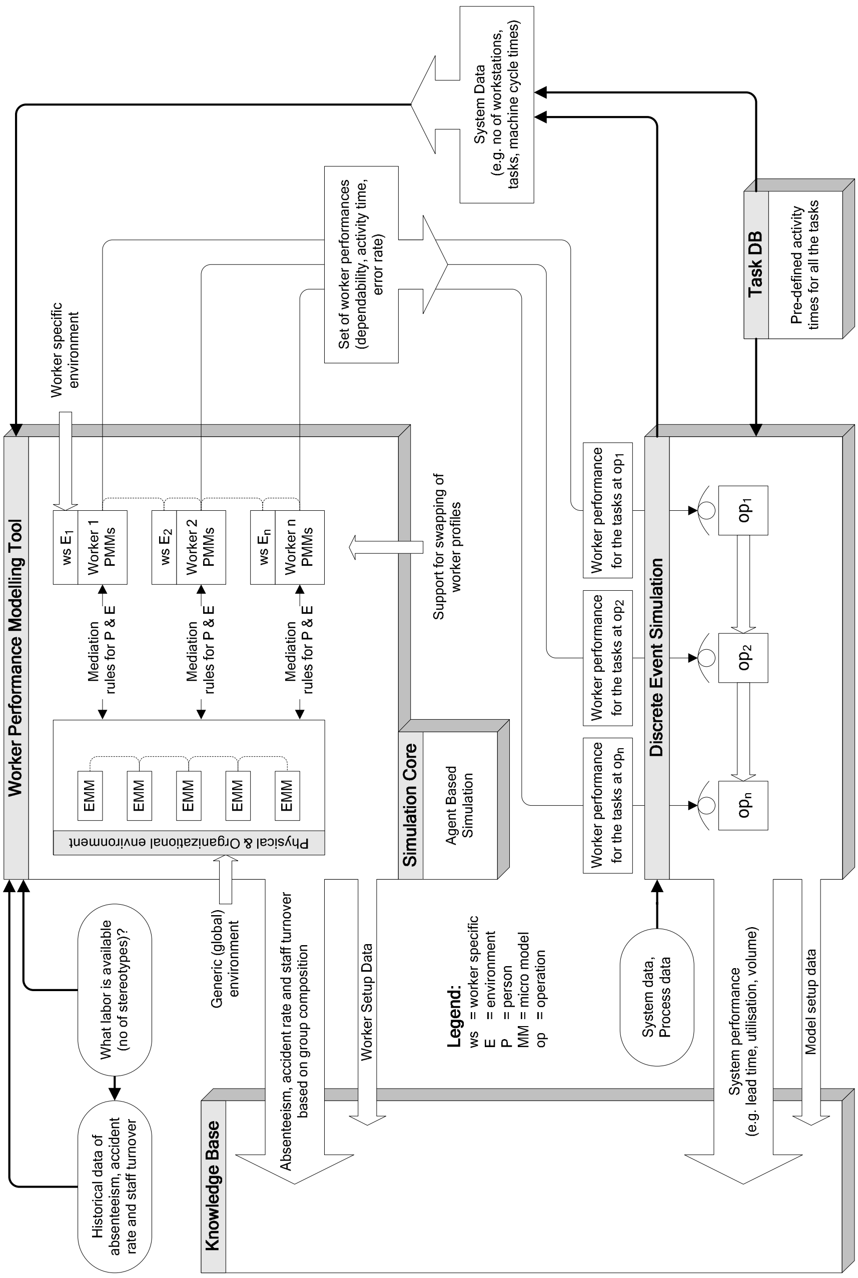

Figure 5: Tool development after step 3; Situation based approach

As this is the final tool, the elements and its manner of operation are described in more detail. The WPM tool consists of worker agents, local environment agents and a global environment agent. Each worker agent represents a worker entity from the DES model and is linked to a local environment agent that represents the specific environmental conditions at a particular workplace. The WPM tool has its own simulation core which makes it independent from the DES model. The global environment consists of a collection of micro models representing physical and operational environmental factors. As an input, the WPM tool would require static information about the profile of the workforce and historical data about absenteeism, accident rate and staff turnover. Additional dynamic information from the DES model about the task to conduct and the state of the system is also needed. As an output the WPM tool delivers the values for a set of direct worker performance indicators consisting of activity time, error rate and dependability for each individual worker. Furthermore, at the end of each simulation run, probability values for indirect worker performance indicators that reflect worker wellbeing consisting of absenteeism, accident rate, and staff turnover are estimated and stored in a knowledge base together with the setup data of the workforce.

The DES model would typically be one developed in a visual interactive modeling system that allows some form of programming. Connected to this DES model would be a task database which includes all the predefined standard times for the tasks to be conducted by the workers. At each event that significantly changes the state of the system, and might therefore have an impact on worker performance, a set of system state data is sent to the WPM tool. This data is sent in combination with a request for a set of worker performance data that reflect worker reactions to the new situation. At the end of each simulation run, the system performance data (e.g. productivity) is stored in a knowledge base together with the setup data of the DES model. Once the knowledge base has been populated with a reasonable quantity of cases, it could be used to try and identify emergent patterns. It might be possible to derive rules that describe how a certain system setup impacts on different workforces or how a certain workforce reacts to different system setups.

4.2 Choosing a Worker Agent Architecture

Before considering which factors and state descriptors are needed for a worker agent, a decision must be made as to what underlying agent architecture to use. This is because different architectures require different categories of factors and state descriptors. There are many ways to design the inner structure of an agent and many different agent architectures have been developed over the years. Wooldridge (1999) classifies architectures for intelligent agents into four groups, as represented in Table 2. Furthermore, the table contains some examples of concrete agent architectures for each class with reference to some of their key contributors.

Class	Examples of concrete architectures
Logic based agents	Situated automata (Kaelbing, 1986)
Reactive agents	Subsumption architecture (Brooks, 1986)
Belief-Desire-Intention agents	BDI architecture (Bratman et al 1988)
Layered architectures	Touring machines (Ferguson, 1992)

Table 2: Classification of agent architectures (after Wooldridge, 1999)

For the purpose of modeling human behavior, Schmidt (2000) proposes PECS (Physique, Emotion, Cognition, Social Status) as a new reference model, which aims to replace the BDI (Belief, Desire, Intention) architecture. He argues that the BDI structure is not appropriate for modeling real social systems as it conceives human beings as rational decision makers while in reality their decisions are controlled by reactive and deliberate behavior. As these are attributes that we want to represent, for the moment the PECS reference model will be considered to be the most suitable one for our purposes.

4.3 Worker Agent State Descriptors

In order to design a worker agent it is necessary to investigate what factors influence direct worker performance. These factors could be used as state descriptors in form of state constants, state variables and state transition functions if they are definable, tangible, quantifiable, and can be evaluated. Some models and frameworks that might be of help in giving indications for such factors have been developed in Occupational Psychology and Organizational Behavior research, and are applied in Job Design and Human Resources. A selection of these are now described and discussed with regards to their usefulness in terms of offering ideas for worker agent state descriptors.

A classical model of person-environment interaction is provided by Lewin (1935) which states that Behavior (B) is a function of interactions between the Person (P) and the Environment (E) at any given time or situation: B=f(P,E). Lewin's theory stresses the importance of understanding behavior within the total situation and his model accounts for the natural variability of behaviors between different situations. It is now commonly accepted that person and system factors influence work behaviors (Williams & Fletcher, 2002). Unfortunately, the model is of a very general nature and the challenge is to find the relevant factors for B, P and E and their mediation rules.

Support for defining the relevant factors for B, P and E may be found in modern job design models. Das (1999) has attempted to integrate an extensive list of modern industrial job design factors into a single comprehensive model. Unfortunately, there are some substantial weaknesses in this model: it does not elaborate on how factors interact within the workspace to influence the specific outcomes and it does not weigh any of the factors pointed out with a degree of importance to define their impact. Das (1999) himself indicated that it will be extremely difficult to collect all the empirical evidence to determine the effects and interactions of the various work design factors.

A model proposed by Parker et al. (2001) provides categories rather than a universal list of variables in order that specific factors can be identified according to a context. One of the advances of the model is that it considers basic pre-design conditions that may influence the effect of job design on performance outcome. The model which accounts also for the stages in which factors come into play includes a range of mediating mechanisms, antecedent factors and contingencies that might affect the impact of work characteristics.
Silverman et al. (2001) states that performance moderator functions could be used to increase the realism of human behavior models and expresses at the same time that the modeling and simulator communities are finding it difficult to extract performance moderator functions from the behavioral literature. He offers a list of moderators that reflect significant dimensions of individual and group differences as well as external stressors on individuals and/or groups.

A model presented by Furnham (1992) displays some of the main factors of individual differences that influence occupational behavior and how they relate to one another. He explains that the basic assumption of this model is that any act or behavior pattern of a specific individual can be accurately predicted from the linear addition of scores on various factors like personality, abilities and temporary states, together with some measures of situational or environmental conditions. These factors are all weighted in accordance with their importance for the specific criterion behavior that is being predicted. This makes a number of assumptions: all relevant variables are specified, correct weightings can be obtained, no situational modifiers and linearity.

The problem with all the models presented so far is that they are either of a very general nature, and therefore do not support the decision about relevant factors and variables, or their variables are indefinable and intangible constructs that would be difficult to quantify and evaluate in practice. Moreover, all of the models neglect to fully consider aspects of the physical environment, which can be an important consideration within a factory environment.

A theoretical framework has been developed by Hadfield et al. (2002) which seems to offer a solution to the problem. Figure 6 shows the framework that is based on the Lewin model mentioned earlier and has been specifically tailored to represent factory workers and their impact on system performance. The framework provides a unified approach, and identifies the main factors and performance measures for worker behavior through an extensive review and synthesis of the relevant literature using a criterion-based evaluation concerning: general relevance, contextual relevance, robustness of evidence and measurability. However, the problem regarding the usability of the theoretical framework for the development of the worker agents is that it lacks a definition of state transition functions. These are key components of an agent framework. Therefore, with respect to its inability to consider time related changes of the state of the worker throughout the day, it will be a useful help but cannot be used directly in order to define the inner structure of a worker agent.

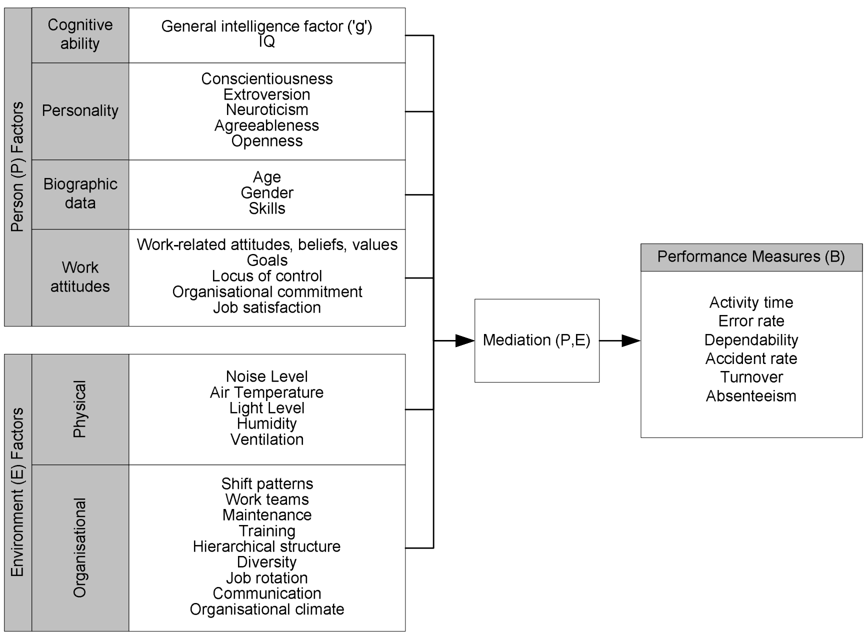

Figure 6: Theoretical framework for worker performance modeling (Hadfield et al., 2002)

4.4 *Conceptual Design of a Worker Agent Framework*

Finally a worker agent framework is presented in Figure 7. It is based on the PECS reference model structure (Schmidt, 2000) and on the theoretical framework for WPM (Hadfield et al., 2002) introduced earlier in the chapter.

The theoretical framework has been enhanced for this purpose by state transition functions that have been derived from discussions with other researchers. In addition to the state variables and state transition functions of the original PECS reference model, the proposed worker agent framework includes state constants which describe factors such as biographic data and personality. Here, changes over time are assumed to be irrelevant as simulations are usually only run for periods in which these factors do not change drastically. This is a significant development over the original reference model where such constants are not considered.

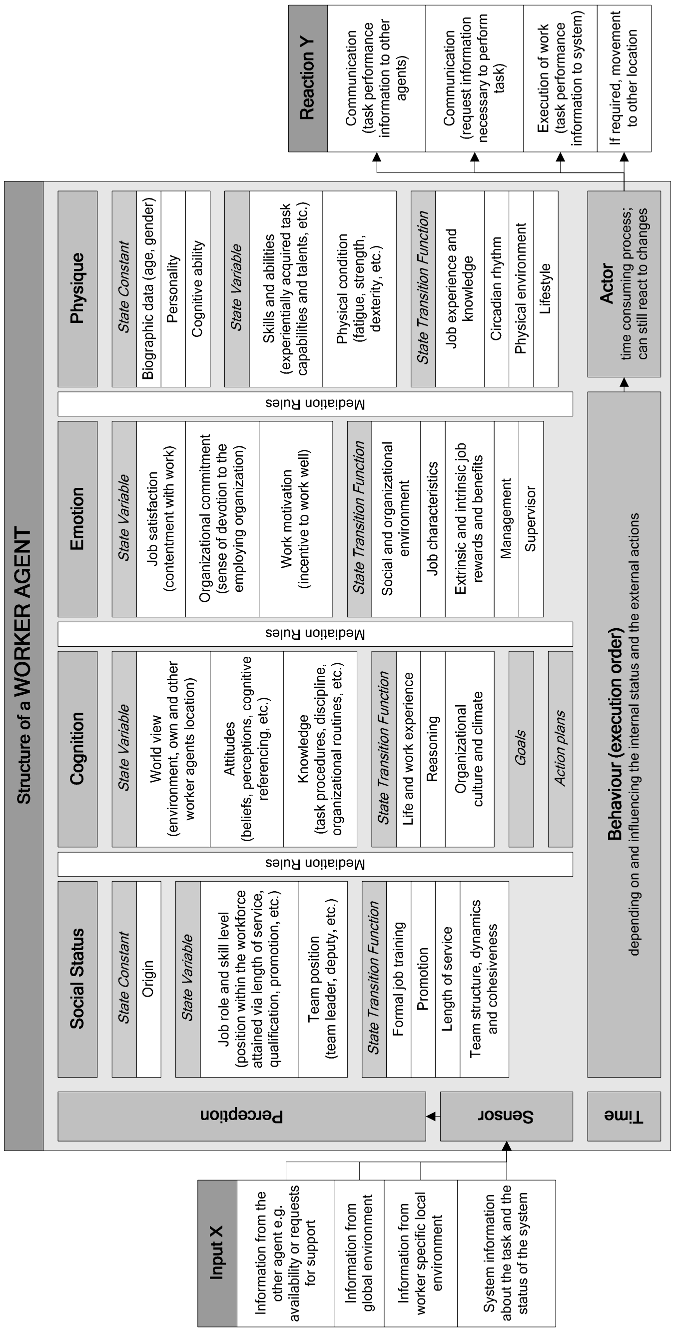

Figure 7: Concept of a worker agent

4.5 Problems with Implementing the Agent-Based Approach

Currently, the agent paradigm is not used in manufacturing system simulation for the purpose of modeling human behavior. In addition, multi-agent based simulation is not yet accepted as a mainstream simulation technique in the manufacturing industry. Many problems and much resistance arise if one wants to adopt the paradigm into the context of manufacturing system simulation.

The main issue that has been identified is the complexity of the task, as worker agents would not just be used for testing a specific limited hypothesis which is often the motivation when agents are used in Social Sciences. Rather they would be used to analyze a variety of manufacturing systems and therefore they must be designed to be valid in a much broader sense which inflates their complexity.

Another major problem still remains and this concerns the collection of sufficient data to populate the framework. Data that links an individual worker to his or her performance is required, but the old fashioned industrial engineering approach of using time studies to set pay rates or extract more effort from workers has "poisoned the well for this activity" (Baudin, 2002). Therefore, it will be very difficult to collect the required empirical data in order to populate the worker agents. Another source of information would be social and behavioral science literature. Here, the difficulty is that mainly specific problems including only a very limited amount of factors are investigated and the required mediation rules that would link all the factors within the framework are not known.

Finally, there are some technical issues. The agent concept is very appropriate for time driven simulation but less appropriate for event driven simulation which is commonly used in manufacturing systems design. DES models do not support the agent concept of proactiveness, since they are designed as reactive models. However, this is an important aspect when modeling human performance as humans are able to take initiatives and act without external stimuli.

5 Conclusions

The focus of nature inspired computing is most often related to problem solving and involves the study of natural phenomena, processes for the development of computational systems and algorithms capable of solving complex problems. A second less recognized objective, which has been the focus of this chapter, involves the modeling of natural phenomena and their simulation in computers. The goal in this direction is to devise theoretical models, which can be implemented in computers, faithful enough to the natural mechanisms investigated so as to reproduce qualitatively and/or quantitatively some of their functionality.

The first part of the chapter has demonstrated the importance of incorporating HPV models into human oriented manufacturing system simulation models and thereby enhancing the capabilities for simulation experts to represent the behavior and predict the performance of these systems more accurately. The second part of the chapter has focused on the requirements for a multi-agent based approach to WPM. After carefully considering the possible development stages of a WPM tool, the choice of a suitable architecture for the worker agents, and the choice of state descriptors for direct workers a new worker agent framework has been proposed. Finally, problems expected to occur upon implementation of the proposed MAS have been discussed. Two major roadblocks have been identified in the development of the proposed solution: first, the complexity of the task and second, data collection problems.

In order to tackle the complexity issue it is suggested to take a step back and keep the KISS (Keep It Simple, Stupid) principle in mind when implementing the proposed worker agent. The required approach is to design a very simplistic agent at first that only considers a few of the relevant state descriptors and once these are under control gradually enhance the complexity of the agent. Advances in the development of visual interactive multi-agent simulation platforms now make it a lot easier to design the agents step-by-step and at the same time allow experimentation with them. Software packages such as AnyLogic (XJ Technologies, 2005) allow the implementation of agents in a very comfortable way as long as the required state descriptors and mediation rules are known. Notably, this particular package is a multi-paradigm simulation solution which allows the execution of hybrid models consisting of continuous and discrete elements and so supports the integration of agents into DES models.

With regards to the data collection problems, here is a thought to stimulate discussion. How about an alternative approach to Figure 7 using an Artificial Neural Network (ANN) internally to relate the dependent (performance measures) and independent (person and environment factors) variables? The assumption is that such an approach could somehow help to overcome the problem of defining all the mediation rules required to mediate between different factors. This assumption is based on an explanation of deployment areas of ANN by Francis (2001) who states that “such a data mining tool can fit data where the relationship between independent and dependent variables is nonlinear and the specific form of the nonlinear relationship is unknown”. This would be the case for most of the factors listed in the theoretical framework presented earlier in Figure 6. An ANN is also effective in dealing with two additional data challenges: correlated data and interactions (Francis, 2001). Externally this agent-like framework would have the same input and output variables as the worker agent. An example of such an approach applied in the field of industry dynamics is presented by Yildizoglu (2001) who uses ANNs within his firm agents to model the expectations conditioning the R&D decisions of firms.

Finally it has to be recognized that the limitations in representing HPV do not only affect manufacturing systems simulation but in fact any system simulation where people play a key role. Simulation models in management science and operations research often represent complex systems that involve people, as for example in call centers and hospitals. An advance in modeling these people in terms of their behavior is expected to improve the value of simulation as a decision support tool for these application areas as well.

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Key Terms & Concepts

Agent Based Modeling: In context of this chapter it is a bottom-up approach which allows the behavior of human beings to be captured in a more realistic fashion. The artificial agents acting as representatives for real factory workers have to be designed to mimic the attributes and behaviors of their real-world counterparts as similarly as possible. The system's macro-observable properties emerge as a consequence of these attributes and behaviors and the interactions between them.

Artificial White Room: Simulation of a laboratory as it is used by Social Scientists for data gathering under controlled conditions.

Direct Performance Indicators: Indicators which measure how the individual worker affects the system. Typical indicators are activity time (the actual time it takes a worker to complete a task which is usually a repetitive cycle), error rate (an indication of how well a worker conducts a task), and dependability (given that all conditions for a task to commence are met, when does the operator start the activity in response to a request?).

Direct Workers: Factory workers dedicated to predominately manual routines.

Discrete Event Simulation (DES): Modeling of a real system as it evolves over time by representing the changes as separate events, for the purpose of better understanding and/or improving that system.

Human Performance Variation (HPV): The variation in the time taken to complete a task by a direct worker under normal working conditions.

Indirect Performance Indicators: Indicators which measure how the system affects the workers, which in return might have an effect on the performance of the individual worker. Typical indicators are absenteeism (absence from the workplace for any reason other than official leave or those covered by collective agreements), accident rate (an indication of how safely the worker conduct their work), and staff turnover (the number of employees starting or finishing employment at a particular place of work over a given period).

KISS (Keep It Simple, Stupid) Principle: A popular maxim often invoked when discussing a design process as a reminder to avoid the unnecessary complexity that can arise during the design process.

Time and Motion Study: An analysis applied to a job or number of jobs to check the efficiency of the work method, the equipment used, and the worker. Each operation is studied minutely and analyzed in order to eliminate unnecessary motions and thus reduce production time and raise output, which increases productivity.

Worker Performance Modeling (WPM): Modeling of the processes and effects of human behavior within a working environment.