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AI and OR in Management of Operations: History and Trends

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ABSTRACT

The last decade has seen a considerable growth in the use of AI for operations management with the aim of finding solutions to problems that are increasing in complexity and scale.

This paper begins by setting the context for the survey through a historical perspective of OR and AI. An extensive survey of applications of AI techniques for operations management, covering a total of over 1200 papers published from 1995 to 2004 is then presented.

The papers are categorised into four areas of operations management: (a) design, (b) scheduling, (c) process planning and control and (d) quality, maintenance and fault diagnosis. Each of the four areas is categorised in terms of the AI techniques used: genetic algorithms, case based reasoning, knowledge based systems, fuzzy logic and hybrid techniques.

The trends over the last decade are identified, discussed with respect to expected trends and directions for future work suggested.

Keywords: Operations Management, Artificial Intelligence

1. INTRODUCTION

The 1980s saw a significant growth in research in Operations Management including scheduling, project planning, fault diagnosis and maintenance, aimed at improving the efficiency and effectiveness of operations management. These research areas remain the subject of many conferences, journals and research programmes. So at first sight, it appears that the problems remain unsolved despite the significant investment in attempts at finding solutions by academia, industry and governments. There are several reasons for this apparent lack of progress: (a) many of the solutions formulated in the 1980's were for well defined situations; (b) the solutions assumed that accurate data was available for the models; and (c) the solutions were too computationally expensive to be practical.

In addition to these, the world has changed dramatically since the 1980s, with businesses operating in a global market, in an environment that results in problems that are more complex and on a larger scale than ever before. On reflection, therefore, it should not be surprising that, on their own, our old solutions are inadequate for today's problems in operations management.

One approach to the kind of problems we face in operations management today, was proposed by Simon (1987), who, in his keynote paper "Two heads are better than one" proposed the use of a combination of Operational Research (OR) and Artificial Intelligence (AI). This combination seemed natural to Simon, who appreciated the complementary strengths of the two disciplines, with OR strong on well founded mathematical models and AI strong on heuristics.

This potential has been recognised by both communities, with an increasing number of publications at the OR-AI interface. In recent years, there have also been conferences, such as the European Conference on Intelligent Management Systems in Operations that has been organised by two of the authors (KAHK & SV) since 1997 with the aim of bringing together researchers from both communities. These conference have provided the motivation for the authors to survey the field and identify the progress being made, trends and areas of future work (Meziane *et al.* 2000; Proudlove *et al.* 1998). The 2005 conference provided an appropriate time to carry out the most comprehensive survey to date that is based on much more data and over a longer time period than any of the authors' previous surveys. The survey aims to address the following questions:

(a) What is the current direction of research on applying AI techniques in Operations Management?
(b) What are the trends in terms of utilising particular AI techniques for sub-problems in Operations Management?
(c) What should the future direction of research be?

To answer these questions, the authors survey papers published from 1995 to 2004, and indexed in Elsevier's Science Direct (http://www.sciencedirect.com/, accessed February 2005) which covers over 1800 journals in Science, Technology and Medicine.

The paper begins by setting the context for the survey in section 2, where a historical perspective of Operations Research and Artificial Intelligence is presented. Section 3 presents an overview of the type and range of research on applying AI in Operations Management by citing representative and innovative work. Section 4 discusses the results obtained, identifying areas of major application, historical trends and areas that need future research.

2 CHARACTERISTICS OF OR AND AI

OR flourished during the second world war in military applications and thereafter as a result of the development of the electronic computers. The term OR was first used about 1936, though decision models can be traced back to the beginning of the 20th century. During the period from the fifties to the seventies, it expanded into Industry and Government, aided in the UK by nationalisation policies and in the US as a result of OR scientists moving to industry despite the large defence contracts (Ackoff and Sasieni 1968).

Many definitions of OR have been offered and, equally, many arguments that suggest why it cannot be defined (e.g, by Ackoff and Sasieni (1968)). However, a widely accepted textbook view of OR is that it is characterised by: (a) the application of a scientific method (b) interdisciplinary teams and (c) applied to complex problems.
A central part of the scientific method, is the adoption of the following phases of OR (Decision) methodology (White 1975):

(a) Primary Problem Formulation Phase.
(b) Object System Model Phase.
(c) The Solution.
(d) Implementation.

In many ways, OR is closely related to the area of System Identification (SI) though it is seldom that this fact is referred to in the literature. SI is the determination of a system within a specified class of systems to which the system under test is equivalent, on the basis of input and output (Zadeh 1962).

Eykhoff (1974) suggests that the SI methodology consists of the following main steps:

(a) Selection of a model structure.
(b) Fitting of parameters to data.
(c) Verification and testing of model.
(d) Application of the model to its purpose.

Both OR & SI apply the Scientific Method (hypotheses, experimentation, analysis). SI is concerned with physical and engineering systems that are usually subject to basic laws of physics. If a system is complex, then a black box approach can be used (e.g, using frequency response). OR is usually concerned with "Problem Solving" of complex socio-economic and management systems. One can argue that SI can be viewed as a special case of OR. OR can feed back experiences to help solve very complex physical/engineering systems (e.g., multiphase turbulent flow)(Kobbacy 1981).

Russell Ackoff has been advocating that OR should return to its original mission of serving executives rather than playing with mathematics and adopt a system orientation. He criticised OR in a series of papers on the grounds that OR provides solutions as opposed to "Synthetic Thinking" which aims at problem dissolution through design (Ackoff 1979a; Ackoff 1979b; Ackoff 2001). He also stressed that OR is preoccupied with efficiency, not effectiveness i.e., with doing things right rather than doing the right things.

In contrast, the type of problems tackled in Artificial Intelligence are influenced by the direction set by its pioneers, McCarthy, Turing and Michie who set a challenge that can be summarised by the following quote from Turing's seminal paper (Turing 1950) :

> "I believe that at the end of the century the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted. "

Thus early research in AI aimed to tackle problems that were considered to require intelligence, such as playing Chess. Despite initial excitement in the 1960's, the 1970's saw a quiet period for AI following the publication of a negative review of AI in the Lighthill report (1973). The 1980's saw a resurgent AI, with significant investment in Japan on the 5th Generation Computer Systems project that aimed to develop parallel machines based on logic (Feigenbaum and Shrobe 1993), which was followed by a response from the UK with its Alvey programme (Oakley and Owen 2000) and sustained investment in a number of AI related projects by the European Strategic Programme of Research and Development in Information Technology (ESPRIT).

The majority of AI applications in the 80s tended to be static and suffer from the Feigenbaum Bottleneck (Feigenbaum 1977) where both the development of the system and the quality of the end system were heavily dependent on the ability to elicit and represent expert knowledge. More recently, there has been a much greater focus on machine learning, with research aimed at improving decision tree learning algorithms, case based reasoning, genetic algorithms, neural networks and artificial immune systems.

Given these different goals and directions, it is not surprising that OR and AI have each resulted in techniques that have complementary properties. The following table summarises some of the characteristics of the OR/AI techniques and their differences.

TECHNIQUES	PROPERTIES
OPERATIONAL RESEARCH	
Mathematical Programming	Optimisation
Network Analysis/PERT/CPA	Project Planning
Regression	Forcasting
Queuing theory	Service models
Simulation	What-if scenarios
Maintenance Models	Planning replacement
ARTIFICAL INTELLIGENCE	
Logic and Theorem proving	Deduction and Inference
Production Systems, Semantic nets,Frames, Objects	Representation of knowledge
Uncertainty Management (Bayes, Fuzzy logic)	Capable of reasoning under uncertanty
Case Based Reasoning	Capable of reusing experience to solve problems

Data mining and Symbolic Learning	Discovering new relationships and models. Capable of aiding model and knowledge acquisition
Neural Networks, GAs	Capable of learning how to classify, cluster and optimise.
Heuristic Searching methods (e.g. A*)	Capable of finding good solutions quickly in a large search space
Intelligent Agents	Capable of encapsulating a wide range of properties including autonomous and proactive behaviour.

Table 1: AI and OR techniques and their properties.

As the above table suggests, the range of techniques and their properties are quite different. As Fordyce, Norden and Sullivan (1987) point out, this is surprising since there is evidence that the Operational Research Community did have an early interest in the kind of problems that the AI community have addressed. Most notably, they refer to Simon and Newell's seminal paper "Heuristic Problem Solving: The next advance in operations research" that appeared in Operations Research as long ago as 1958. Fordyce et al. (1987) go on to explain two reasons why the OR community did not take up the challenges set by Simon and Newell: (a) a lack of computational power and memory that made it difficult for OR researchers to tackle problems that were "knowledge rich" and (b) there was a lack of "mathematical niceness" that OR practitioners were trained to require.

Fortunately, the AI community had its own reasons for studying and solving the kinds of problems that together with the traditional OR discipline has led to a significant amount of research since the 1980s. The following sections present the results of the survey which enable reflection upon the major areas of effort, their effectiveness and where furture research should focus.

3 SURVEY AND REPRESENTATIVE RESEARCH

This section presents the survey examining the use of AI techniques in various parts of operations management. The framework for the survey has evolved from that used by the authors in their previous surveys. In the 1998 survey, the authors extended Schroeder's (1993) framework which defined four major categories for decisions, namely: process, quality, capacity and inventory. In the 2000 survey, the focus was on applications in manufacturing and used Rao *et. al.'s (1993)* framework, which has the following six areas: (a) design, (b) scheduling, (c) quality management, (d) maintenance & fault diagnosis, (e) process planning and (f) process control. These categories worked well in the 2000 survey and initially, they were adopted for this survey but extended to include service as well as manufacturing operations. An additional category for knowledge management, which was expected to be a growth area, was also added. However, as the survey proceeded, these categories seemed to be too fine, making it difficult to distinguish papers between some of the related categories. In particular, and perhaps not surprising in hindsight, papers on process planning, control, inventory management and supply chain management were closely related, and papers on quality, maintenace and fault diagnosis were also related. Surprisingly, there were hardly any papers on the use of AI techniques in knowledge management, making its use as an additional category redundant. Thus, although the use of the seven categories seemed appropriate initially, in practice, it made better sense to merge the closely related areas to ensure that the categorisation of papers was sufficiently accurate and there were an adequate number of papers in each category for any trends to be meaningful. Hence, for the purposes of this survey, the following four major categories were utilised:

- Design
- Scheduling
- Process Planning and Control (including inventory and supply chain management)
- Quality, Maintenance and Fault Diagnosis

As indicated in Table 1 above, there are several categories of AI techniques, some well established and others, such as dynamic Bayesian networks and temporal data mining, still growing in importance in operations management. The techniques we selected to focus on were those that would enable a ten year survey: Case Based Reasoning (CBR), Genetic Algorithms (GAs), Neural Networks (NN), Knowledge Based Systems (KBS), and Fuzzy logic, all of which have been established for over a decade. Data mining was also considered as a possible area but, once we decided to have the categories of NN, and GAs, there were very few papers applying techniques such as association rule mining in operations management to produce any sensible trends over the last decade. As well as the established AI techniques, we were also interested in the use of a combination of the AI techniques and hence added a category, called hybrid.

The methodology adopted was simple and involved using fairly obvious keywords to search the Science Direct Database to identify references in chronological order. The number of papers considered was large and the process of filtering and classification of the papers was time consuming, resulting in the classification of over 1200 papers. Each identified paper was then classified according to the area and technique used. There are three important points to note about the classification process:

- Although most of the classifications were reasonably clear, some inevitably required our judgement. For example, some of the papers would mention design in general terms several times but would not be about design processes or about the design of products.
- Having identified maintenance as part of a separate area, papers on scheduling maintenance activity were categorised under maintenance and not scheduling.
- Papers that used a hybrid approach were not double counted, so for example, papers that used GAs and NNs together were counted just once, under the hybrid category.

The following subsections present an overview of the use of AI techniques in each of the four areas of operations management by citing representative and innovative work. Some relevant papers that appeared, or are in press in 2005 are included in the description, though later, they are omitted from the statistics when considering the 10 year trends. Section 4 presents an analysis of the results and discusses current and future trends.

3.1 DESIGN

3.1.1 CBR and Design

Case Based Reasoning (CBR) aims to provide a memory of past experience in the form of reusable cases. CBR is therefore very appropriate for reusing past designs, resulting in savings in comparison to design from first principles. To date, the majority of systems utilizing CBR are in retrieving past designs, such as designs of reactive distillation systems (Avramenko *et al.* 2004), offshore well designs (Mendes *et al.* 2003), hydraulic production machine design (Vong *et al.* 2002), design of antibiotic therapy regimens for patients in critical care (Heindl *et al.* 1997), ship designs (Lee Dongkon and Lee Kyung-Ho 1999), designs of low power transformers and design of software (Paek *et al.* 1996; Praehofer and Kerschbaummayr 1999).

Many design problems involve trying to optimise parameters or a trade-off between parameters in order to meet the problem requirements. CBR has been used in a few such applications, including design of materials to meet product requirements (Amen and Vomacka 2001; Mejasson *et al.* 2001), and the design of chemicals that meet safety and environmental requirements (King *et al.* 1999).

Given the general success of the use of CBR that has been reported in conferences such as the International Conference on CBR, it is perhaps a little surprising that there hasn't been a significant growth in their use for design. Applications that aim to utilize past design strategies, promote discovery of designs and innovation appear not to have materialized. Though there are some interesting papers in the 1990's on the use of CBR for inventive design (Ishikawa and Terano 1996), the process of aiding innovation (Faltings and Sun 1996), and on creative design (Kolodner and Wills 1996) these studies appear not to have been followed up.

One reason for this lack of growth might be that most applications of CBR rely on the availability of very similar cases and leave the subsequent adaptation of the retrieved design to the human designer. More research on adaptation may therefore be needed if the range of applications that would find CBR useful is to increase.

3.1.2 GAs and Design

A major strength of GAs is their ability to evolve near optimal solutions to non-linear optimisation problems. Hence they have been widely used in the design of structures and materials where strength and safety requirements that are non-linear need to be met. Examples of applications in this area include the design of multi-storey steel frames (Kameshki and Saka 2001; Kameshki and Saka 2003), their use to design alloys to meet user requirements (Kulkarni *et al.* 2004), and their use to design reinforced concrete (Leps and Sejnoha 2003; Rafiq and Southcombe 1998).

GAs have also been advocated for drug design though, surprisingly, only a few papers have been published in this area, including their use in tools for drug design (Hou and Xu 2001) and some review papers (Park *et al.* 2004; Terfloth and Gasteiger 2001).

The use of GAs to meet various criteria including safety requirements has been reported in several studied (Cantoni *et al.* 2000; Jo and Gero 1998; Matsuzaki *et al.* 1999; Osman *et al.* 2003).

An interesting use of GAs is in providing designers with a tool in which they can use GAs to explore alternative designs interactively by guiding the evolution process. Examples include the aesthetic design of dams (Furuta *et al.* 1996), design of fashionable clothes (Kim and Cho 2000) and using user guided breeding in CAD (Graham *et al.* 2001).

3.1.3 Neural Networks and Design

The primary use of artificial neural networks in the last decade has been in drug design and design of materials. Drug design represents more than a third of the neural network applications in design. Many of these focus on using the predicative power of the backpropagation algorithm to help quantify structure-activity relationships (Kovesdi *et al.* 1999; Polanski *et al.* 2002; Polanski *et al.* 2000; So and Karplus 1997; Terfloth and Gasteiger 2001). Other uses include optimising release of drugs such as aspirin (Ibricacute *et al.* 2003; Sun *et al.* 2003; Wei *et al.* 2001) and the pursuit of therapies for AIDS (Cai *et al.* 1998; Sardari and Sardari 2002).

Applications in engineering design also represent about twenty percent of the uses of neural networks in design, though the range of applications is more variable. Applications include designing concrete structures (Adeli and Park 1995; Cladera and Mari 2004; Deng *et al.* 2003; Dias and Pooliyadda 2001; Hadi 2003), design of cold-form steel (Adeli and Park 1995; El-Kassas *et al.* 2001; El-Kassas *et al.* 2002; Karim and Adeli 1999) and the design of polymers (Zhang and Friedrich 2003).

Novel applications include the use of NNs to aid design by features in computer integrated manufacturing (Ding and Yue 2004), design of catalysts (Huang *et al.* 2001; Huang *et al.* 2003; Liu *et al.* 2001; Sasaki *et al.* 1995) and the design of digital aids that provide reminders for people with dementia (Mihailidis *et al.* 2001).

3.1.4 KBS and Design

Despite scepticisms about the use of expert systems or KBS in the early 1980's, the volume of publications on the successful application of KBS is impressive. The majority of applications are in engineering and construction. These include a diverse range of systems such as those for the design of automotive engine components (Sapuan *et al.* 2002), design of elevator systems (Motta *et al.* 1996; Rothenfluh *et al.* 1996) design of digital filters (Cappellini *et al.* 1995), bridge design (Moore *et al.* 1997; Shiva Kumar *et al.* 1995), design of offshore structures (Soh and Miles 1995), design of water retaining structures (Chau and Albermani 2003), design of relief vents for dust explosions (Vadera *et al.* 2001), layout of ship engine rooms (Lee *et al.* 1998) and several systems that aid design of buildings (Gonzalez-Uriel and Roanes-Lozano 2004; Mohamed and Celik 2002).

There are also several KBS systems that support concurrent engineering, a process that looks at the full design and development cycle of products (Laring *et al.* 1996; Xue *et al.* 1999; Zha and Du 2002). However, given the importance of concurrent engineering, it is surprising that there are few follow up studies post-2002.

There are fewer applications of KBS in design outside engineering, but include a system for the design of dentures (Davenport *et al.* 1996), use of KBS for curriculum design (Wilcox 1996) and a system to support the design of data bases (Storey *et al.* 1998).

3.1.5 Fuzzy Logic and Design

Design is usually based on imprecise criteria and the use of fuzzy logic therefore offers very relevant methods to enable optimisation of parameters to meet requirements.

Feng (2001) (Feng *et al.* 2001) studies how requirement can be mapped to fuzzy relations. Tang *et al.* (2002) and Karsak(Karsak 2004) develop systems that enhance Quality Function Deployment (QFD) with fuzzy linguistic terms to represent design requirements and which enable assessment of the extent to which design requirements are met. Design of products to meet personal requirements such as look, feel and taste represents an interesting use of fuzzy logic that is explored by Cai *et al.* (2003) for product appearance, by Park and Han (2004) for the design of office chairs, by Hanson (Hanson *et al.* 2003) for design of car interiors and by Sigman and Liu (2003) for modelling non-functional requirements for software design and development.

3.1.6 Hybrid Approaches in Design

The FL/NN combination is the most popular hybrid combination for design. Hsiao and Huang (2002) use a FL/NN approach to establish relationships between product-form parameters and image descriptors which can then be used by designers to generate products meeting desirable customer requirements. Sun (2000) uses a combined NN and fuzzy inference approach to rank alternative designs based on customer requirements. Zha and Lim (Zha and Lim 2003) use a fuzzy neural network that is capable of taking account of operator posture and movement for the optimal design of manual assembly workstations.

Though not as popular, the GA/NN combination has also been used in design, for example, in the design of catalysts, where a NN is used to model interactions and a GA is used to design and optimise a catalyst (Huang *et al.* 2003).

Despite the popularity of KBS in design, they are rarely used in combination with other techniques for applications in design. One of the few studies that utilises the KBS/NN combination is by Zakarian and Kaiser (1999) who use it to support optimisation of parameters in computer-aided design.

3.2 Quality, Maintenance and Fault Diagnosis

3.2.1 CBR in Quality, Maintenance and Fault Diagnosis

The survey did not find any published papers in quality management or maintenance that use CBR. Only a few publications were found in fault diagnosis, including two papers on the use of CBR in locomotive diagnostics: (Varma and Roddy 1999) and (Vingerhoeds *et al.* 1995). Xia and Rao (1999) argued for the need to develop dynamic CBR, which introduces new mechanisms such as time-tagged indexes to help solve problems that need to take into account system dynamics and fault propagation phenomena. Cunningham *et al.*(1998) describe an incremental CBR mechanism that can initiate the fault diagnosis process with only a few features.

3.2.2 GAs in Quality, Maintenance and Fault Diagnosis

Applications of GAs in quality management are limited to a few examples, including the development of a river water quality management model (Kapanoglu and Miller 2004), a management system for damaged concrete bridges in Japan (Miyamoto *et al.* 2001) and in the more classical quality management area of the design of control charts (Celano G. and Fichera S. 1999).

GAs are more popular in maintenance because of their robust search capabilities that help reduce the computational complexity of large optimisation problems. Thus there are applications in nuclear power plants (Pereira and Lapa 2003), and in the area of safety related systems to assure a high level of reliability (Martorell *et al.* 2004). Preventive maintenance scheduling optimisation is another popular area where GAs have been used and includes the areas of chemical process operations (Tan and Kramer 1997), nuclear systems (Lapa *et al.* 2000), power systems (Huang 1998), single product manufacturing production line (Cavory *et al.* 2001) and mechanical components (Tsai *et al.* 2001).

GAs have attracted moderate interest over the past decade for fault diagnosis, with applications in nuclear power plants (Yangping *et al.* 2000) and electrical distribution networks (Wen and Chang 1998).

3.2.3 NNs in Quality, Maintenance and Fault Diagnosis

NNs are the most popular AI technique applied in the areas of quality, maintenance and fault diagnosis. In quality management, there has been a few publications on predicting and management of quality of river water, watershed, groundwater and costal water (Aguilera *et al.* 2001; Chen *et al.* 2004; Hong and Rosen 2001). Other applications include the use of NNs to predict performance of design-build projects (Ling and Liu 2004) and the management of secure communication systems (Karras and Zorkadis 2003).

NNs have many applications in the area of predictive maintenance and more specifically in condition monitoring. An interesting application, developed by Garcia et al. (2004), uses NNs to aid tele maintenance, where staff can carry out the work remotely and in collaboration with other experts. Other applications of NNs in condition monitoring include the work of Bansal (Bansal *et al.* 2004)et al. on machine systems, Booth and McDonald (1998) on electrical power transformers, Luxhoj (Luxhoj 1998) on turbine flow-meters and Spoerre (1997) on bearings. Shyur *et al.* (1996) use NNs to predict component inspection requirements for ageing aircraft and Eldin and Senouci (Eldin and Senouci 1995) use NNs for the condition rating of joint concrete pavements.

As mentioned earlier, NNs are very popular for fault detection and diagnosis. They have been discussed since the late 1980s for model based fault detection and isolation, particularly when analytical models are not available. In an early review paper on use of AI in fault diagnosis, Frank and Koppen-Seliger (1997b) indicated that the goal of fault detection is to detect the fault and its causes early enough to avoid overall system failure. They defined 3 steps for fault detection (i) residual generation, i.e., generation of a signal that reflects the fault, (ii) residual evaluation, i.e., the logical decision making on the time of occurence and location of the fault and (iii) fault analysis i.e., determination of the type of fault, its size and cause. For using NNs in fault diagnosis, they have to be trained for both residual generation and evaluation using collected or simulated data for the former and residuals in the latter. The major difficulty of using NNs in fault detection is the lack of analytical information on the performance, stability and robustness of the network.

There has also been a strong interest in using NNs for fault diagnosis in the chemical process industry, for example in fault diagnsis of packed towers (Sharma *et al.* 2004), complex chemical plants (Ruiz *et al.* 2001b), and batch processes (Scenna 2000).

3.2.4 KBS in Quality, Maintenance and Fault Diagnosis

There is continued growth and interest in the applications of KBSs in quality management. Chin *et al(Chin et al. 2003).* have developed a knowledge based self assessment system to measure organisational performance based on a renowned Business Excellence Model and Stein *et al.* (2001) have developed a KBS to support implementation of the American Disability act in a University. Other applications include use of KBSs for evaluating watershed processes with respect to ecological states (Reynolds *et al.* 2000), quality assessment in the food industry (Stein and Miscikowski 1999) and for auditing processes in quality assurance systems (Bayraktar 1998).

We found only a few papers in the area of KBS in maintenance management in the past decade. Of particular interest is the study by de Brito *et al*. (de Brito *et al.* 1997) which developed a prototype system for optimising the inspection, maintenance and repair strategies for bridges.

There have been many applications of KBS in fault diagnosis, including rotating machinery (Yang *et al.* 2005), induction motors (Acosta *et al.* 2005), CNC machine-tools (Leung and Romagnoli 2002), industrial gas turbines (Milne *et al.* 2001), reactors (Varde *et al.* 1998), electrical power distribution systems (Baroni *et al.* 1997; Teo and Gooi 1997), monitoring green house sensors (Beaulah and Chalabi 1997), coal washing plant (Villanueva and Lamba 1997), chemical processes (Batanov and Cheng 1995; Joo Mo *et al.* 1997; Nam *et al.* 1996), and in robotic systems (Patel *et al.* 1995).

3.2.5 Fuzzy Logic in Quality, Maintenance and Fault Diagnosis

Apart from a couple of papers on identification of river/stream water quality, we found no other publications for FL in quality management. Similarly we located very few papers on using FL in maintenance, including the work of Al-Najjar and Alsyouf (Al-Najjar and Alsyouf 2003) on using fuzzy multiple criteria decision making and that of Jeffries *et al(Jeffries et al. 2001).* which presents a fuzzy approach to condition monitoring of a packaging plant.

Using FL in fault diagnosis involves fuzzifying residuals, evaluating residuals using inference and then defuzzifying them (Frank and Koppen-Seliger 1997a). There are a wide range of application areas for FL in fault diagnosis. These include fault diagnosis of thrusters for an open-frame underwater vehicle (Omerdic and Roberts 2004), railway wheels (Skarlatos *et al.* 2004), Chemical processes (Dash *et al.* 2003; Ruiz *et al.* 2001a), analog circuits (El-Gamal and Abdulghafour 2003) and rolling element bearings in machinery (Mechefske 1998) .

3.2.6 Hybrid Approach in Quality, Maintenance and Fault Diagnosis

There are several applications that utilise a combination of CBR and KBS systems in quality. Humphreys *et al.* (2003) combine CBR, KBS and multi-attribute analysis (MAA) to evaluate supplier environmental management performance. CBR/KBS hybrid systems are utilised by Cheung *et al.* (2003) for performance management and monitoring in customer services, by Lee *et al.* (1999) in clinical incident management to improve quality of care and Foong *et al.* (1997) uses CBR/KBS in intelligent help desk fault management.

There are only a few studies that make use of hybrid systems for fault diagnosis. Amongst these, the FL/KBS combination is the most common, including the work of Zhao and Chen (2001) on diagnosing concrete bridge deterioration, Ortega (Ortega and Giron-Sierra 1998)and Giron-Sierra's research on automated servicing of a space station and Tarifa and Scenna's (2004; Tarifa and Scenna 2004) work on fault diagnosis. Jota *et al.* (1998) used neuro-fuzzy techniques and a KBS for fault detection in service power transformers

Yang *et al.* (Yang *et al.* 2004) (2004) integrated NN with CBR to enhance fault diagnosis by using CBR to search for similar previous cases. Ozyurt *et al*. (1998) have developed a hybrid symbolic-connectionist machine learning approach for fault diagnosis in a hydrocarbon chlorination plant. Frank *et al.* (1997a) and Tyan *et al.* (1996) have developed hybrid NN/ Fuzzy logic systems for fault diagnosis. Luxhoj and Williams (1996) present a hybrid NN/ KBS DSS for aircraft safety inspection.

3.3 SCHEDULING

3.3.1 CBR in Scheduling

The primary use of CBR in scheduling is in job shop scheduling and is typified by the CasePlan (Dzeng and Tommelein 2004) and CABIN (Miyashita *et al.* 1996) systems. Both systems show the feasibility of retrieving similar past cases and adapting them to solve job shop scheduling problems.

3.3.2 GAs in Scheduling

The last decade has focused on six major areas of applying GAs to scheduling problems: job shop scheduling, scheduling of tasks on multi-processors, labour scheduling, scheduling vehicles and forest management.

The development of products requires sequencing of jobs to machines in a way that minimizes tardiness and makespan. The last decade has seen many attempts at using GAs for single products (Adamopoulos and Pappis 1998; Caraffa *et al.* 2001; Iyer and Saxena 2004; Knosala and Wal 2001; Kurz and Askin 2004; Mattfeld and Bierwirth 2004; Nearchou 2004; Wang and Xue 2002), and for multi-objective problems (Cardon *et al.* 2000; Oh and Wu 2004). Determining an opitimal batch size can also be a significant factor for production lines, and some authors, notably (Khouja *et al.* 1998; Sarker and Newton 2002), use GAs to address this problem.

The advent of parallel machines and multi-processor computers results in analogous problems to job shop scheduling, except that tasks need to be allocated to different processors and throughput needs to be optimised subject to the availability of processor and memory constraints. Aguilar and Leiss (2004) study this problem for shared memory systems and several other authors propose alternative approaches for scheduling processes on multiprocessors (Ahmad and Dhodhi 1996; Oh and Wu 2004; Tsuchiya *et al.* 1998). Braun *(Braun et al. 2001)* presents a comparison of eleven heuristics for scheduling tasks onto distributed computing systems.

The problem of making the best use of staff with different experience and capabilities is a key to the success of any organization, whether it is in the health service, academia or production. The studies reported by Cai and Li (2000) and Easton and Mansour (1999) consider this problem in a general context, while Aickelin and Dowsland(Aickelin and Dowsland 2004) (2004) develops a GA based system for scheduling of duties for nurses.

Vehicle scheduling problems often go beyond minimizing distance, incorporating different service level requirements for different customers and levels of costs. Baita (Baita *et al.* 2000)presents the limitations of a traditional approach and compares it to the use of GAs. Malmborg (1996) presents the use of GAs to meet service levels, and Taniguchi and Shimamoto (2004), present a GA based scheduler for the dynamic scheduling of traffic that uses real time information.

Although not as extensively used as the in the above areas, the use of GAs in management of forests and irrigation is interesting. Moore *et al.* (2000) use GAs to examine the effects of different policies on the populations of birds and extinction rate. Ducheyne *et al.* use GAs to assess the effects of different management policies on the even-flow forest management problem.

3.3.3 Neural Networks in Scheduling

Of the different neural network algorithms, the Hopfield and Boltzman machines are considered the most suitable for optimisation problems. The Hopfield model is the most widely used in scheduling, with applications in job shop scheduling (Foo *et al.* 1995), its use to schedule generators (Dillon and O'Malley 2002) and to schedule the broadcasting of packets in a multihop packet radio network (Li-Chiun Wei and Chang 1997). Though the Boltzman machine is regarded as an improvement over the Hopfield model, in that it avoids local minima, we did not find any papers that utilise them directly for scheduling.

Though less suitable for optimisation, feed forward neural networks have also been used. For example, Ben-Nakhi and Mahmoud (2002) uses feed forward neural networks to predict the optimal settings for air conditioning so as to minimise energy utilisation.

An interesting use of feed forward networks is to aid scheduling by predicting parameters such as tardiness and lead times and then using higher level search procedures that utilise this capability to evaluate alternative proposed solutions and optimise schedules (Fonseca and Navaresse 2002; Park *et al.* 2000).

3.3.4 KBS in Scheduling

The use of KBS in scheduling is small in comparison to the use of GAs. Example uses include providing construction managers with a tool for exploring alternative schedules that take into account resources, material selection and costs (Mohamed and Celik 2002), its occasional use in job shop dynamic scheduling that aims to achieve load balancing on machines for a flexible manufacturing plant (Zhang and Chen 1999), the scheduling of railway freight loadings (Geng and Li 2001) and determining schedules of breathing pressures for pilot masks based on antropometric and physiological information so that pilots don't fall unconscious (Yeow *et al.* 2002).

3.3.5 Fuzzy Logic in Scheduling

In most practical scheduling problems, due dates, processing times and even constraints are not precise and hence fuzzy logic and set theory have been widely used in scheduling and project planning. Several authors have developed algorithms for the single machine job shop scheduling problem with fuzzy due dates and processing times, including (Adamopoulos and Pappis 1996; Chanas and Kasperski 2001; Ishii and Tada 1995; Lam and Cai 2002; Muthusamy *et al.* 2003; Sung and Vlach 2003; Wang *et al.* 2002). A useful theoretical result that shows the difficulty of the problem is that minimizing the maximal expected tardiness can be solved in polynomial time whilst minimising the expected maximal tardiness remain NP-Hard when due dates, processing time and tardiness are fuzzified (Chanas and Kasperski 2003).

In the area of project management, Hapke and Slowinski (1996) presents an extension of an existing method for setting priorities for project scheduling under constraints on resources, Wang(Wang 2002) presents a fuzzy beam based search algorithm to develop an algorithm that aims to minimize the risk of a schedule and satisfy temporal constraints.

3.3.6 Hybrid in Scheduling

GAs are good at optimisation, NN's are good at classification or estimation and fuzzy logic is good at modelling uncertainty. Hence combinations of these techniques provide greater power and flexibility in solving scheduling problems. Several authors use GAs to carry out an intelligent search by proposing alternative schedules and then using a NN to assess the quality and fitness of the schedule. A GA then combines the best solution using mutation and crossover operators and then repeating the process to evolve a near optimal solution (Dagli and Sittisathanchai 1995; Lee and Dagli 1997). Fuzzy logic and GAs have been combined effectively for scheduling, where the variables such as due date, processing times and tardiness are modelled using fuzzy sets and the GAs optimise over a fuzzy objective function that minimises tardiness (Kim *et al.* 2003; Peng and Liu 2004; Sakawa and Kubota 2000; Tsujimura *et al.* 1995).

3.4 Process Planning and Control

3.4.1 CBR in Process Planning and Control

Only a few papers were found on applications of CBR in process planning. These include the work of Yuen *et al(Yuen et al. 2003).* to develop a generic computer-aided process planning support system, Lei *et al.* (2001) on applying CBR to cold forging process planning and Chang *et al.* (Chang *et al.* 2000) on indexing and retrieval in machining process planning. Park *et al.* (1998) discuss the use of CBR in process control of complex production processes.

In supply chain management, CBR has been used to develop an intelligent customer-supplier relationship management system Choy et al. .

3.4.2 GAs in Process Planning and Control

GAs have been used in several studies in process planning and optimisation (Drstvensek *et al.* 2004; Lee *et al.* 2002), which in a way overlaps with the scheduling area of application. Senin *et al.* (2000) investigate the application of GAs to concurrent assembly planning. Another interesting area for using GAs in process planning is in setting machinaries e.g. multi-pass face milling (Shunmugam *et al.* 2000) and optimal depth of cut in multi-pass turning (Bhaskara Reddy *et al.* 1998). Vancza and Markus (1996) present a feature-based process planning model which optimises manufacturing costs using a GA.

There are numerous applications of GAs in process control including the elevator cars routing problem (Tyni and Ylinen 2005), control of phosphate processing plant (Karr 2003), control strategy of complex spinning (fibre-yern) production process (Sette *et al.* 1998) and in calibrating computer models of mineral processing equipment (Karr and Yeager 1995).

There has been increasing interest in using GAs as an optimisation technique in inventory management. GAs have been used for allocation of shelf space (Hwang *et al.* 2005), capacitated lot-sizing problem (Xie and Dong 2002) and the inventory management of lumpy demand items (Mak *et al.* 1999). The joint replenishment problem (JRP), which deals with multi-item inventory problems, has been studied using GAs by Chan *et al.* (2003) for multi-buyer situations.

There has been recent interest in applying GAs in reverse logistics and multi-echelon supply chains (Liang and Huang 2005; Lieckens and Vandaele 2005).

3.4.3 NNs in Process Planning and Control

There has been only a small number of publications on the use of NNs in process planning of manufacturing systems. In order to carry out process optimisation, Chambers and Mount-Campbell (2002) develop a neural network metamodel of the components of a system and the entire system is then modelled by interconnecting the NN metamodels. Monostori *et al.* (2000) propose the use of a NN processs model to satisfy requirements of machining at different levels and stages. Santochi and Dini (1996) use NNs in selection of technological parameters of cutting tools.

NNs are a very popular technique used in process control to establish process models. Research projects in recent years have focused on the use of neural networks as a tool for system identification that can deal with nonlinearity (Lennox *et al.* 2001). The main application areas are chemical and process industries and manufacturing. Examples of recent applications include a semi-batch polymerization process (Ng and Hussain 2004), thermal food processing (Torrecilla *et al.* 2004), fermentation processes (Lopes and Menezes 2004), chemical reactors (Yu and Gomm 2003), basic oxygen steel making (Cox *et al.* 2002) and injection molding (Kenig *et al.* 2001). Lennox *et al.* (2001) investigate the industrial application of NNs in the area of process monitoring and control. Azlan Hussain (1999) reviews the applications of NNs in chemical process control. An interesting area in process control, which overlaps with quality control, is the use of statistical process control (SPC) to identify process problems. There has been a number of publications on the use of NNs in SPC including the studies by Al-Assaf (2004), Zorriassatine *et al.* (2003) and Guh *et al.* (1999).

NNs are used to solve a variety of inventory problems in industry. Forest characteristics, tree mortality and predicting forest cover types were studied by Moisen and Frescino (Moisen and Frescino 2002), Hasenauer *et al.* (2001) and Blackard and Dean (1999) respectively. Wang (2001) uses NNs in yield management to adjust price in order to maximise profit in the airline and hotel industries. Baker (1999) studies the assortment problem where demand for any size that is not stocked must be met by supplying the nearest acceptable size. Partovi and Anandarajan (2002) use NNs to carry out ABC inventory classification.

3.4.4 KBS in Process Planning and Control

KBSs have some applications in manufacturing process planing. Zhao *et al* (Zhao *et al.* 2002) describes the integration of KBS with a CAD system and Arezoo *et al.* (2000) present a KBS both for selection of cutting tools and conditions for turning operations. Jiang *et al.* (1999) use an intelligent KBS to generate optimal manufacturing process plans from CAD drawings. Shehab and Abdalla (2001) develop a fuzzy logic based knowledge representation approach that helps in estimating cost modelling of machining processes.

Applications of KBS to process control include the development of a reflow soldering control system (Tsai 2005), control of industrial wastewater detoxication plants (Szafnicki *et al.* 2005), bioprocess control (Hrncirik *et al.* 2002) and multivariate PID control (Ho *et al.* 1998) .

In the area of inventory management, work was developed in the areas of forest ecosystem management (Nute *et al.* 2004) and impact from Chernobyl on Spanish marine environment (Molero *et al.* 1999).

In supply chain management, NNs have been used together with autoregressive methods for improving forecasting and reducing inventory levels and sales failures (Aburto and Weber 2005). Hsieh and Tien (Hsieh and Tien 2004) use Kohonen self-organising maps for the uncapacitated location allocation problem and compare it with the use of simulated annealing.

3.4.5. FL in Process Planning and Control

Karr (1996) discusses adaptive process control and the role of the various AI techniques. Fuzzy Logic is used to manipulate the problem environment, GAs search for more efficient fuzzy membership functions than those used by FL and NNs are used to simulate the problem (as a system identification tool , see section 3.4.3). As such the extensive use of FL in process control (like NNs) is not surprising. Indeed the combined use of FL with NN in particular and GA to a lesser extent is expected.

There are many application areas for FL in process control including the control of gari fermentation plant (Odetunji and Kehinde 2005), basic oxygen furnace (Kubat *et al.* 2004) cheese ripening (Perrot *et al.* 2004), spindel torque for CNC machining (Liang *et al.* 2003), food frying (Rywotycki 2003), flotation column (Carvalho and Durao 2002), combustion control of stoker-fired boilers (Li and Chang 2000) and anaerobic digester in a fluidized bed reactor (Estaben *et al.* 1997).

Samanta and Al-Araimi (2001) present an inventory model based on FL which simulates the DSS to maintain the inventory of a finished product system at the desired level. Bogataj and Usenik (2005) formulated the problem of supply chain coordination using fuzzy sets and compared the outcomes with analytical results. Lin *et al.*(2005) use FL for developing a supply chain agility measure and apply it to evaluate the agility of a Taiwanese company.

3.4.6 Hybrid in Process Planning and Control

There are several hybrid systems that use the FL/GA combination for planning and control, including the work of Acosta and Todorovich (2003) on induction motors, Guillaume and Charnomordic(Guillaume and Charnomordic 2001) in food industry databases, Karr and Freeman(Karr and Freeman 1997) on spacecraft autonomous rendezvous and Tarng *et al.* (1996) in turning operations. Other hybrid applications include a NN/GA system for fruit-storage control (Morimoto *et al.* 1997) and a multiple hybrid system for a cryogenic cooling plant (Linkens *et al.* 2000). The

FL/GA combination has also been used for modelling supply chains where FL is used to determine supply chain uncertainty and a GA is used to determine up to inventory level (Wang and Shu 2005).

Uses of KBS/FL is also very popular in process control. Examples include their use in situ groundwater bioremediation (Hu *et al.* 2003), a system which utilises a FL rule-based inference engine to provide overall control for a bottling plant (Jeffries *et al.* 2003) and knowledge-based supervisory control of a fish processing workcell (de Silva and Wickramarachchi 1998).

Hybrid NN/FL systems have several applications in process control including looper tension control in rolling mills (Janabi-Sharifi 2005), industrial wastewater treatment (Chen *et al.* 2003), logic control for arc welding (Di *et al.* 2001), on-line tool wear estimation (Kuo 2000) and manufacturing process control (Kuo and Cohen 1998). Morimoto *et al.* (1997) present a NNs/ GA hybrid approach for optimal control of a fruit-storage process.

Ming and Mak (2001) use a hybrid GA/NN approach to study tolerance allocation and manufacturing operations selection in process planning.

Du and Wolfe (1997) present details of the implementation of NN/FL systems in industry including inventory. In supply chain management, a hybrid CBR/NN approach has been used for benchmarking suppliers in outsource manufacturing (Choy *et al.* 2002) and for supplier-relationship management (Choy *et al.* 2003)

Examples of multiple hybrid systems include the use of KBS/FL and NNs in control of communication systems (Guyot *et al.* 2004) and aquaculture (Lee 2000), and the use of FL/NN/GA in automation and control of reverse osmosis plants (Zilouchian and Jafar 2001) and cryogenic cooling plant (Linkens *et al.* 2000).

4 ANALYSIS, CURRENT TRENDS AND DISCUSSION

We now discuss the results obtained with respect to the questions raised in the introduction, namely:

(a) What is the current direction of research on applying AI techniques in Operations Management?
(b) What are the trends in terms of utilising particular AI techniques for sub-problems in Operations Management?
(c) What should the future direction of research be?

Rather than attempting to answer these questions by using just the publication rates in some absolute fashion, it is more interesting and revealing to analyse the publication rates with respect to what we might have expected given the known characteristics of the AI techniques and problems. Our personal view of the regions of applicability of OR and AI techniques relative to the decision making level and the extent to which a problem is structured is summarised in Figure 1.

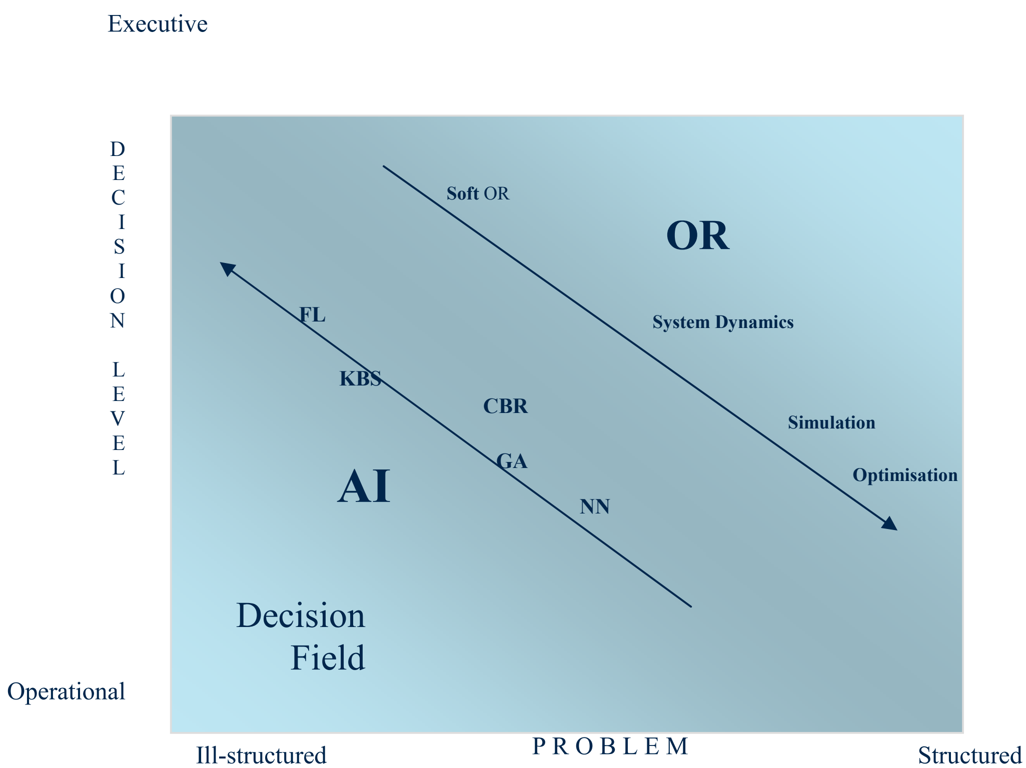

Figure 1: AI and OR Techniques with respect to decision levels and how well a problem is structured and defined.

As problems become more strategic and less well defined, one would expect greater uncertainty in the specification and solution process involved. One would therefore expect fuzzy logic to be more applicable in such circumstances and, hence its position towards the top left of Figure 1. Likewise, knowledge based systems have proved to be very useful for problems that do not necessarily have analytical solutions and can be expected to be placed more towards the top left hand quarter of the Figure 1. Case based reasoning systems retrieve similar past cases to solve a current problem, making them suitable for problems that range from being semi-structured to those that are less structured, hence their more central position. Neural networks and Genetic Algorithms both require identification of a set of parameters and are particularly good for more structured problems that involve classification and clearly defined optimisation problems; hence their position towards the bottom right of the graph.

Where do the four areas of operations management fit on Figure 1? Design is probably the least well structured, often requiring creative thinking to meet vague design goals and is therefore most towards the top left hand corner of the figure. Scheduling is more operational in nature but real-world scheduling involves vague starting times, and goals that are time and context dependent. Hence Scheduling problems are more towards the bottom left hand corner of the diagram. Process planning, control, quality and maintenance tend to be operational and are generally well defined, so we would expect them to be more at the bottom right hand corner of this diagram. How do these expectations compare with the number of publications for each problem area/AI technique? The following table is organised so that the shaded rows and columns correspond to the four corners of Figure 1. That is, if our expectations were followed perfectly, then we would expect highest weights in the top left hand and bottom right hand corners of the table.

	Fuzzy Logic	**KBS**	**CBR**	**GAs**	**NN**	**Hybrid**	**Total**
Design	44	129	53	130	101	52	509
Scheduling	71	32	7	109	19	42	280
Process Planning and Control	37	25	4	28	97	45	236
Quality & Maintenance and Fault Diagnosis	16	26	6	36	93	20	197
Total	168	212	70	303	310	159	1222

Table 2: Number of publications from 1995 to 2004.

There is some correspondence between this table and Figure 1. The top left hand corner of the table shows that there is heavy use of fuzzy logic in scheduling and design, and KBS are used mainly on design problems. In the bottom right hand corner, neural networks are employed in many applications of process planning, control, quality, maintenance and fault diagnosis.

There are also three notable differences from our personal expectations which we discuss below.

First, there is considerable use of GAs and NNs on design problems. Looking more closely at these applications, a third of these applications are about drug design and involve quantifying structure-activity relationships (e.g., (Kovesdi *et al.* 1999; Polanski *et al.* 2002; Polanski *et al.* 2000; So and Karplus 1997; Terfloth and

Gasteiger 2001). A further 20% are applications in Engineering design such as design of concrete structures (Adeli and Park 1995; Cladera and Mari 2004; Deng *et al.* 2003; Dias and Pooliyadda 2001; Hadi 2003), design of cold-form steel (Adeli and Park 1995; El-Kassas *et al.* 2001; El-Kassas *et al.* 2002; Karim and Adeli 1999) and the design of polymers (Zhang and Friedrich 2003). These applications are relatively well defined and therefore explain the use of neural networks and GAs.

A second difference from the expectations suggested in Figure 1 is that, having characterised fuzzy logic as a technology particularly suitable for the executive level and for unstructured problems, their use in process planning and control, an area that we consider to be more operational, may seem surprising. However, many problems in control are relatively well structured in terms of the parameters required, but where the parameters are not precise, hence requiring the use of fuzzy logic. Examples include problems such as controlling an oxygen furnace (Kubat *et al.* 2004) and combustion control of stoker-fired boilers (Li and Chang 2000).

A third difference from our expectations is the relatively low of use of CBR in operations management. As one might expect, CBR is used on design problems such as CAD; however, the use of CBR in the other areas is remarkably low and even in design, there are only a few studied that focus on creative design (Kolodnerand Wills (1996) is a rare exception). This is despite some early successes in the area of scheduling (Miyashita *et al.* 1996) . One possible reason for this limited use of CBR might be that most of the focus by the CBR research community has been on the retrieval phases and not as much effort has been on the more challenging adaptation phase making them less flexible and harder to use to solve the other areas.

We now turn our attention to the question: *what are the trends?* Figure 2 shows the trends for each of the four areas of operations management on a bi-annual basis, from 1995 to 2004.

Both Design and Scheduling has similar trends. The use of GAs is growing substantially and the use of KBS is reducing, perhaps because it is becoming less fashionable and considered to be main stream, rather than research worthy. The underlying problem for both these areas involves optimising an objective function subject to constraints. In the case of scheduling, the objective is typically to minimise tardiness while in design, it is typically to meet user satisfaction on market driven goals. This underlying similarity may explain the similar trends we observe.

Neural networks, particularly the backpropagation algorithm, have been very successful in classification and prediction, and their use for fault diagnosis and quality maintenance continues to grow. Their use in process control and planning peaked in 1990-2000, and has declined somewhat in 2001, but is increasing again. However, neural networks have remained the dominant AI technology for process planning and control throughout the last decade.

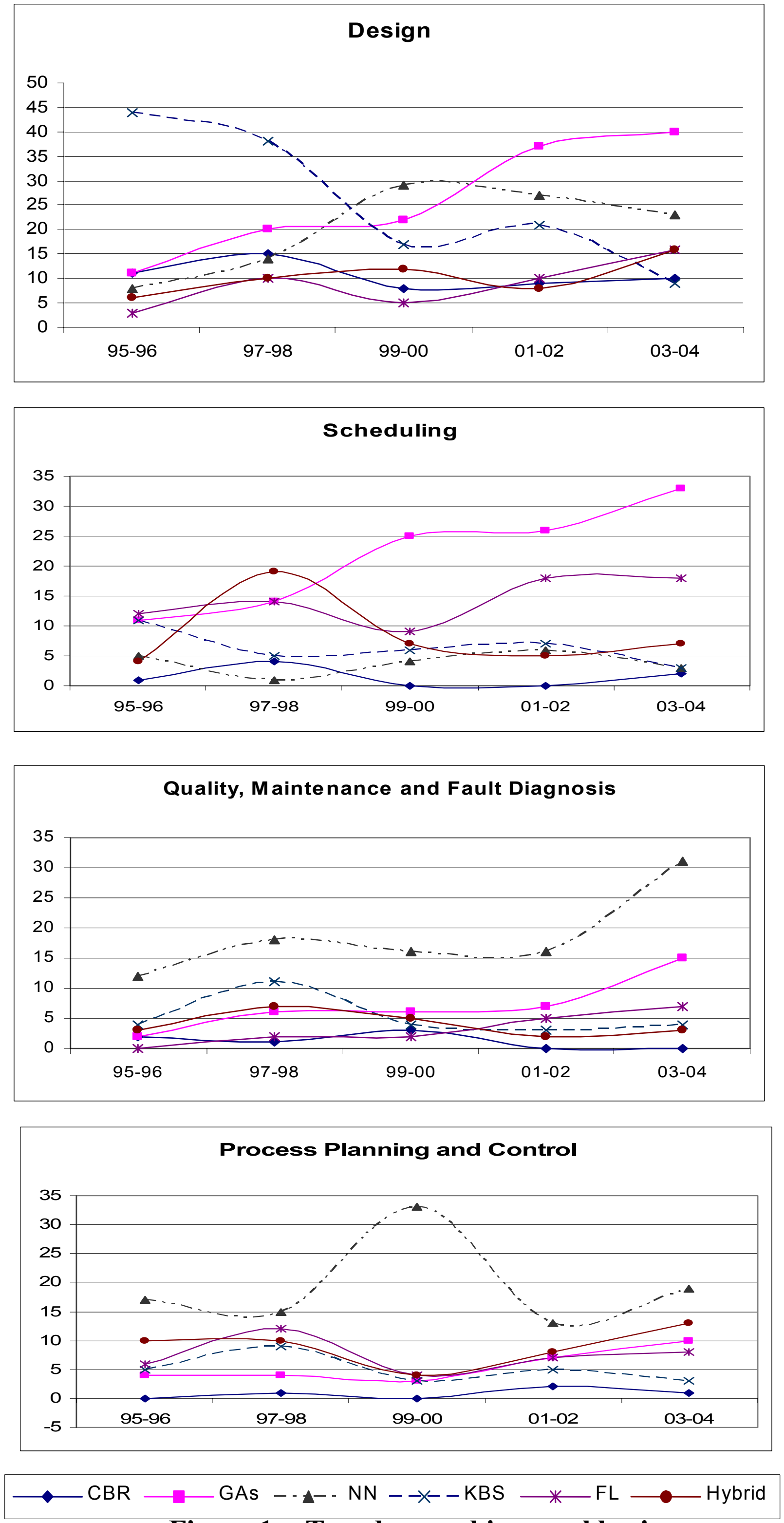

Figure 1: Trends on a bi-annual basis

The last, and most difficult question that we raised is: *What should the future direction of research be?*

As mentioned in the introduction, Ackoff's perceptions, even as long ago as the 70's suggested that there was insufficient work on the executive and less defined problems. The trends above seem to confirm that this lack of focus on the more executive decision making problems has continued in the application of AI in Operations Management. This may be due to the nature of the AI techniques but may also be due to external factors, such as pressures on academics to publish, forcing a preference for quantity rather than innovation. Individual AI techniques have shown their power and range of effectiveness, such as the use of GAs in scheduling, but extending the range of problems that can be solved using AI techniques may well require using the combined power of hybrid systems. Although there are some very good examples of the uses of hybrid approaches, such as the use of neuro-fuzzy controllers, the number of publications is surprisingly low and there is no clear increasing trend. Integrating hybrid approaches in a way that takes advantage of the capabilities of different technologies is a non-trivial task and the development of a framework or an agent-based architecture to support a dynamic and cooperative approach to solving problems in operations management seems the natural way forward if the field is to go beyond the kind of problems we know can already be solved.

4 CONCLUSION

This paper has surveyed the application of AI techniques in the area of operations management, covering over 1200 papers since 1995. The survey confirms various trends, some that one might expect, and others that are less expected:

- There is heavy use of fuzzy logic in design and scheduling
- Neural networks are dominant in process planning and control.
- Many drug design applications utilise neural networks and GAs
- There is surprisingly low use of case based reasoning other than in design

In terms of trends, there is a decline in publications that describe applications that use KBS, perhaps because it is now less fashionable and research worthy. There is a definite increasing trend in the use of GAs in all areas and most notably in scheduling.

There is no apparent growth in the use of hybrid approaches that take advantage of the strengths of different AI techniques and there appears no further progress in moving towards using AI techniques for problems, such as creative design, that are more challenging. These remain relatively unexplored areas of research that we hope the community will pursue.

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