Chapter 1

Introduction

The hallmark of modern civilization is the massive industrial infrastructure that provides its daily needs of goods and services in a timely, efficient and affordable manner. This massive industrial infrastructure is basically a conglomeration of various types of interdependent and mutually complementary industries. Each industry tries to achieve the objective of providing either raw materials for some other industries or produce finished products for direct human consumption, at the lowest cost with the minimum input of resources in the least possible time. Therefore, while on one hand, timely availability of raw material at each stage is an essential requirement, and on the other hand, the machines themselves need to be maintained in a timely and efficient manner to ensure continuity and equilibrium between the mutually dependent industries.

The importance of availability of raw material in a timely way, exactly at the point of consumption cannot be over-emphasized. However, apart from the basic cost of the raw material itself, there are also inherent elements of costs built into each and every activity that is carried out for the above purpose. Further, there are various types of uncertainties, the primary one being uncertainties in demand of final product, which affects the costs associated with the entire production cycle. Therefore, every industry always tries to minimize the total cost associated with the processing, procurement and storage of inventory.

With the progress of time, modern machines have increased functionality and associated complexity. Large machinery system consisting of a large number of interdependent machines has become the order of the day. In such chains and network of a large number of machines, untimely and unexpected stoppage of any machine on account of a breakdown, which could be due to lack of a simple activity like lubrication, has a detrimental effect on other machines that work in conjunction with each other. The effect can have a much serious repercussion in service industry like a modern communication network. Hence, it is imperative to ensure that machines must not break down in an untimely and uncontrolled manner, by providing timely maintenance inputs in the most economical way.

A detailed discussion on inventory control, preventive maintenance scheduling, and joint preventive maintenance scheduling and spare parts inventory control has been presented in the following sections. A thorough literature review has been carried out. The motivation behind this study has been discussed, and the aims and objectives of this present study have been stated. This chapter ends with an organization of the thesis.

1.1 Inventory Control

One of the key decision variables in any inventory model is the Economic Order Quantity (EOQ). EOQ is the optimal order quantity that minimizes total inventory cost, which includes holding, ordering and backordering (if any) costs. In general, the cost of raw material varies in the range of 70% to 80%, of the final value of a product being manufactured. Since the cost towards inventory has a major share in the cost of the final product being manufactured, proper scientific control of inventory is necessary to minimize production expenses. The fundamental model of inventory was developed by Harris in 1913 [1], and extensively applied by Wilson [2]. The underlying assumptions in the fundamental EOQ model is that demand for a product is known and constant, and that each new order is delivered instantaneously, whenever inventory reaches to zero. Holding cost is taken as a certain percent of raw material cost. Ordering cost is kept fixed and considered to be independent of the number of units ordered.

However, in actual practice, the costs of holding, ordering and backordering are always likely to vary from one cycle to another. Not only the cost of purchasing raw material but also the demand may vary from time to time as well. The absence of historical data makes it difficult to estimate the probability distribution of these variables. Thus, on account of the uncertainties involved, fuzzy set theory is better suited for the analysis of inventory. Therefore, to ensure minimum expenses towards inventory in an uncertain environment, analysis can be done considering the holding cost, ordering cost and backordering cost (if any), and the demand to be fuzzy in nature. The utility of such analysis, wherein the various parameters are considered to be fuzzy in nature (to reflect real industrial situations more closely) can be checked by verifying the results suggested by the fuzzy model through real data collected from industry.

1.2 Preventive Maintenance Scheduling

To obtain maximum production/continuous service from a machine, it is imperative that not only the machine is to be inspected from time to time but also adequate resources are to be kept in place to make the machine functional in case of breakdown(s). Breakdown of a machine would not only result in direct losses like loss in production/unavailability of a service, but also result in consequential situations like chocking of production lines and loss of customer goodwill due to unavailability of product or service. Many maintenance models like breakdown maintenance, age replacement, block replacement, periodic replacement and many others, are being followed for various types of machines. For the large complex machines, most common to modern production and service industries, the best practice would be to maintain machines in a preventive fashion, so that not only losses due to sudden breakdown are controlled, but also adequate availability is ensured at all the times.

With the above background, preventive maintenance models were also studied in this work. If preventive maintenance of a machine is carried in such a way that the machine becomes “as-good-as-new”, it would be called Prefect Preventive Maintenance. On the other hand, if minimal repair is carried out just to make the machine functional, like repairing a punctured tyre of a public transport bus, it would be "as-bad-as-old". In practice, however, whenever maintenance of any type is carried out, condition of the machine after maintenance would be in between "as-good-as-new" and "as-bad-as-old". The above type of maintenance would be called Imperfect Preventive Maintenance. Moreover, on account of aging of various machine elements/parts, a machine would require more frequent maintenance, as it would become older. For example, a new car would require less frequent maintenance in its first few years, however with its age, it would require more frequent maintenance. Therefore, complex machines require sequential preventive maintenance, and the maintenance so carried out is, in general, imperfect.

Sequential Imperfect Preventive Maintenance model, so constructed for a machine/system, could be optimized for various parameters like minimization of the time to repair, maximization of the availability, or minimization of total cost toward maintenance in a given period of time. The most useful parameter, which needs to be optimized could be the mean cost rate of the system, which can be alternatively understood as the total expected cost towards various types of maintenance offered to a machine over its useful service life divided by its total expected lifetime. On account of various parameters involved, traditional optimization methods require lengthy implementation procedures. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) algorithm could alternatively be used for carrying out the optimization. The suitability of the model can be tested and the solutions suggested by non-traditional optimizers can be evaluated by applying the techniques so developed, to actual scenarios in an industry.

1.3 Joint Preventive Maintenance Scheduling and Spare Parts Inventory Control

As discussed earlier, it is imperative that not only inventory cost be minimized, but also vital machinery must be kept in good working condition at all times. While on one hand, it is the most essential that large complex machines be provided with preventive maintenance in a systematic way from time to time to arrest any chance of sudden breakdown resulting consequential losses; on the other hand, an effective policy for adequate stock of spares as backup, is also required to ensure timely repairs and reasonable availability of machines. Therefore, a modern industry needs to not only ascertain maintenance schedules that would minimize the total expected cost rate towards preventive maintenance related expenses, but also simultaneously develop policies for adequate and timely procurement and stocking of inventory of maintenance spare parts, so that the joint cost of operating a large complex machinery is minimized.

An attempt was made to combine the two objectives of minimizing preventive maintenance cost rates and minimizing the cost towards inventory of spare parts into a single objective, and carry out optimization of the joint model. On account of the various parameters involved in the joint optimization process and the necessity of length algorithms/semi-numerical procedures, as viable alternatives, GA and PSO algorithms may be suitable for carrying out the joint optimization. Industrial data can be gathered and the model can be applied to the same, to find out if real and tangible benefits become feasible by carrying out joint optimization of the cost towards preventive maintenance and that towards inventory of maintenance spares.

1.4 Literature Review

This section details the studies conducted by various investigators on inventory control, preventive maintenance scheduling and the joint model. Apart from a historical prospective, there is a discussion on contemporary work in the above three fields as well.

1.4.1 Studies on Inventory Control

The study on inventory control has been carried out in two parts. In the first part, inventory control is studied while the demand is kept fixed, which is followed by investigations into situations, where the demand varies with time in the second part.

1.4.1.1 Models with Fixed Demand

Inventory control is an important field of operation management. A proper control of inventory can significantly enhance a company's profit. In 1913, EOQ formula was introduced by Harris [1]. Fuzzy set theory introduced by Zadeh [3] in 1965, had been applied for realistic modeling of inventory control system. Several attempts were made by various investigators to study and optimize inventory models, and some of those are discussed below.

In 1982, Kacprzyk and Staniewski [4] applied the fuzzy set theory to inventory control problem and considered a long term inventory policy making through fuzzy decision models. An algorithm was also presented to find the optimal time-invariant strategy for determining the replenishment to current inventory levels that optimized the membership function. Uncertainty in inventory control had been solved using fuzzy knowledge-based system by Petrovic and Sweeney [5] in 1994. Fuzzy numbers had been used to represent uncertain data and relations between them modeled by fuzzy if-then rules. A literature survey on applications of fuzzy set theory in production management till 1997, was carried out by Guiffrida and Nagi [6].

Schniederjans and Cao [7] in 2000, compared inventory ordering under Just-In-Time (JIT) and EOQ, and concluded that JIT could be superior to EOQ in inventory ordering purchase. Moon and Lee [8] studied the effects of inflation and time-value of money on EOQ model with random product life cycle. They developed a quantitative model, which could serve as a useful tool for managerial decision making in 2000. In 2003, Wu and Yao [9] studied fuzzy inventory with backorder for fuzzy order and shortage quantities. They used triangular fuzzy membership function distributions in their study, and found that fuzzification of both order and shortage quantities could give better results than fuzzifying any one variable. Yao and Chiang [10] investigated inventory model without backorder with fuzzy total cost and storing cost in 2003. They defuzzified the total cost so obtained by centroid and signed distance methods. Triangular and trapezoidal fuzzy numbers were used in their investigation. Chang [11] applied fuzzy set theory to EOQ model with imperfect quality items in 2004. He developed a model for determining optimal lot size with fuzzy defective items and fuzzy annual demand.

Adida and Perakis [12] used fluid models for optimization of inventory models dealing with demand uncertainty. However, in their model, they did not consider backorder. In 2006, investigations had also been carried out for multiple commodities as dynamic programming model, where genetic algorithms followed by neural networks were trained to approximate the optimal cost function on a randomly generated sample set by Gao and Feng [13]. Maiti et al. [14] utilized a real-coded genetic algorithm (RCGA) for multi-item deterministic inventory control system having two separate storage facilities (owned and rented warehouse) in 2006. Shortages were not allowed in the model developed and investigated by them. Syed and Aziz [15] considered an inventory model without shortage under fuzzy environment in 2007. Ordering and holding costs were considered as fuzzy triangular numbers, and optimum order quantity was calculated using signed distance method for defuzzification. In 2007, Wang et al. [16] developed the model of fuzzy economic order quantity without backordering. Holding cost and set-up cost were considered as fuzzy in nature and the model was developed for determining the credibility of total cost in the planning period to be below some predefined budget. Vijayan and Kumaran [17] investigated continuous review and periodic review inventory models under fuzzy environment, where the membership function distribution took a trapezoidal form.

In 2009, Chou [18] proposed a fuzzy economic order quantity (FEOQ) inventory model, where costs and quantities were expressed using trapezoidal fuzzy numbers. They studied defuzzification technique for the fuzzy economic order quantity inventory model using (a) Function Principle (b) Graded Mean Integration Representation and (c) Kuhn-Tucker conditions. The utility of the model was demonstrated by a numerical example. Maiti and Maiti [19] studied inventory-distribution system for an item with multi-level warehouses and retailers in 2009, with the twin objectives of (i) maximizing customer service and (ii) minimizing inventory related total cost of the system including total transportation cost. Mahata and Goswami [20] investigated EOQ by taking the demand rate, lead-time and inventory costs as fuzzy numbers. Multi-item mixture inventory model, in which both demand and lead time were random, along with a budget constraint was investigated by Bera et al. [21]. Fuzzy chance-constrained programming technique was utilized in their investigation. The fuzzy parameters were transformed into corresponding interval numbers and the interval objective function were, thereafter, transformed into classical multi-objective EOQ problem.

Wang [22] investigated a mixture inventory control system, in which various parameters like lead time demands in different cycles, defective rates of arrived order, various ordering costs etc. were considered to be independent and identically distributed random variables. A fuzzy simulation algorithm and an iterative algorithm were designed to minimize the expected total annual cost. Mahata and Mahata [23] applied fuzzy EOQ model to supply chains in the year 2011. Rong [24] developed EOQ model by treating the holding cost, shortage cost and ordering cost per unit as uncertain variables.

Pathak and Mondal [25] investigated EOQ inventory model for a deteriorating item with ramp type demand in fuzzy stochastic environment with random Weibull distribution under inflation and time value of money over a finite planning horizon. The holding, purchasing, shortage, lost, selling, and ordering costs were represented by triangular fuzzy numbers, whereas the demand rate and net inflation rate were taken as trapezoidal fuzzy numbers. Bjork [26] investigated uncertainty in production process with asymmetric triangular fuzzy numbers. More recently, Hsu and Hsu [27] developed an integrated inventory model for vendor-buyer cooperation for imperfect production process and had shown that an integrated model could result into appreciable cost reduction for both in comparison to independent decision making by the buyer alone. Ameli et al. [28] utilized laws of thermodynamics to EOQ model in 2013. Inflation and discount rates were taken as fuzzy numbers to account for uncertainties, and a mathematical model was presented to maximize the total earnings.

1.4.1.2 Models with Variable Demand

A discussion on attempts by various investigators to study and optimize inventory models, wherein the demand varies over different procurement cycles is presented below.

Inventory control by optimal policies for controlling cost rates in a fluctuating demand environment was investigated by Song and Zipkin [29] in 1993. Variation in demand due to causes like economic recession etc., was modeled by Brill and Chaouch [30] in 1995. Kao and Hsu [31], and Dutta et al. [32] studied single period inventory model with fuzzy demand and fuzzy random variable demand, respectively, and developed models for optimum order quantity in terms of cost. A literature survey on models for production planning under uncertainty till 2006, was carried out by Mula et al. [33].

Gallego et al. [34] analyzed variation of base stock levels for inventory under normal, log-normal and gamma and negative binomial distributions-type demand. The products, whose demand could be manipulated by artificially restricting supply were studied by Sapra et al. [35]. Fuzzy inventory model of deteriorating items could be developed by Jadhav and Bodkhe [36], however, they did not include shortages in their model. Singh et al. [37], and Malik and Singh [38] utilized soft computing techniques for modeling of inventory under price dependent demand and variable demand, respectively. Halim et al. [39] developed production planning models for fuzzy demand rate. Trapezoidal fuzzy numbers were considered in the analysis.

Variation in demand due to fuzziness and randomness was modeled by Nagare and Dutta [40] in 2012. They developed an expert system, which could determine the optimal order quantity, so that the profit was maximized. Kumar et al. [41] developed fuzzy EOQ models with ramp type demand after taking deterioration of stocked items into account. Fuzzy EOQ model with imperfection, shortages and inspection errors was developed by Liu and Zheng [42], whereas, Saha and Chakrabarti built fuzzy EOQ model for deteriorating items [43].

Modeling of uncertainty in demand was done using linguistic terms by Qin and Kar [44], so that the total expected profit for a fixed time period was maximized. Taleizadeh et al. [45] investigated fuzzy demand under backorder and lost sales by utilizing hybrid method of fuzzy simulation and genetic algorithms. The investigators compared the results with that obtained by fuzzy simulations and simulated annealing, and found that the hybrid method of fuzzy simulation and genetic algorithms could yield better results.

In recent times, Nia et al. [46] investigated multi-item economic order quantity model with shortage under vendor managed inventory policy in a single-vendor, single-buyer supply chain. On account of the fuzziness of the parameters involved, the authors used ant colony optimization to find a nearoptimum solution, which could minimize the total cost of the supply chain. Choudhary and Shankar [47] utilized goal programming model for joint decision making of inventory lot-size, supplier selection and carrier selection. Guchhait et al. [48] developed inventory policy of a deteriorating item with variable demand under trade credit. Management of perishable inventory was investigated by Lee et al. [49].

1.4.2 Studies on Preventive Maintenance Scheduling

Maintenance of a machine after failure is costly, and the machine may remain unavailable for a considerable amount of time. The main difficulty is, how to determine when to preventively maintain a machine before failure. Too frequent maintenance would also not be desirable. It could be better, if a machine is maintained more frequently, as it ages. Such maintenance could be imperfect on account of various factors like inadequate skill of maintenance personnel, pressure to rectify the machine in minimum time, lack of standard spare parts, improper adjustments, and so on. Optimum maintenance policies that could minimize the expected cost rate were studied by Nakagawa [50; 51]. Brown and Proschan [52] developed a model of imperfect maintenance, where a system after maintenance is returned to the "as-good-as-new" state with probability p, or it is "as-bad-as-old" with probability $1-p$. Canfield [53] introduced the concept of system degradation with time. The hazard function was found to approximately follow a two-parameters Weibull distribution.

The two new factors, viz., a_k (improvement factor in effective age) and,

b_k (adjustment factor in hazard rate) were introduced into preventive maintenance models, and sequential imperfect preventive maintenance model was developed by Nagakawa [54]. Jayabalan and Chaudhuri [55] developed a branching algorithm with effective dominance rules that could determine the number of maintenance interventions before a machine would need replacement. The algorithm considered the total cost over a finite time horizon along with inflationary trends. Wang et al. [56] suggested replacement policy for components in a mechanical system. The policy could decide the time for replacement of component(s), where a system would undergo either preventive maintenance or corrective maintenance, where the hazard rate of the system was utilized in the above investigation, and operation profit was the deciding criterion.

After maintenance, a machine may be considered to have become younger in age. This is known as Age Reduction model. Further, the rate of failure of a system decreases after it receives maintenance attention. Alternatively, it can be said that the hazard rate of the machine reduces after maintenance [57; 58]. Optimization algorithms for age reduction model and failure rate models were suggested by Nakagawa [51; 57], where failure time has a Weibull distribution of type $h(t) = \alpha t^{\alpha-1}, \alpha > 1$. Both the models attempted to minimize the expected cost rate. Two factors, viz., a_k (improvement factor in effective age immediately after k^{th} preventive maintenance), and b_k (adjustment factor in hazard rate immediately after k^{th} preventive maintenance) were considered in the models, which could take into account the decrease in age and better reliability of a machine after k^{th} preventive maintenance, respectively. Lin et al. [59; 60], combined both the above models into a hybrid model. The investigators reported that the hybrid model could be more realistic than the stand-alone models. The investigators also reported the results of the hybrid model, where the hazard rate function took a two-parameters Weibull distribution.

Tsai et al. [61] utilized a GA for optimizing maintenance schedules of mechanical components for two types of preventive maintenance, namely, preventive maintenance and preventive replacement. New classes of imperfect repair models, wherein the effect of repair could be characterized in two different ways, viz., a reduction of the failure intensity and a reduction of the system virtual age, were proposed by Doyen and Gaudoin [62]. It was observed that there existed a maximal lower bound for failure intensity of both the models. A study of preventive maintenance schedule that could maximize availability was carried out by Tsai et al. [63]. Sortrakul et al. [64] developed an integrated preventive maintenance planning and production scheduling model, where a single machine had a non-homogeneous Poisson process (NHPP)-type hazard rate. GAs were used by Lapa et al. [65] for preventive maintenance planning based on cost and reliability. The algorithms that could optimize the maintenance schedules for Weibull distribution of type $h(t) = \beta t^{\alpha-1}, \alpha > 1, \beta > 0$, with mean cost rate as the objective, were developed and solved utilizing semi-analytical methods by Bartholomew-Biggs et al. [66]. Horenbeek et al. [67] had detailed various types of maintenance optimization models along with associated criteria. Warranty contracts were incorporated into preventive maintenance policy by Wu et al. [68].

Wu and Zuo [69] reviewed the existing preventive maintenance models, and categorized them into three different classes: linear, nonlinear and a hybrid of both, and investigated the possible extension of the three models along with the statistical properties and optimum preventive maintenance policies. On account of the various uncertainties involved as well as scarcity of failure data, Lin and Huang [70] suggested that a Bayesian decision model, which could utilize all available information effectively, could be better for determining the optimal preventive maintenance strategies. The investigators demonstrated the suitability of the proposed model by utilizing real failure data. Similar results were also obtained by Bell and Percy, who could describe the behavior of a system utilizing Bayesian probabilistic model [71].

More recently, Wang and Lin [72] could utilize PSO algorithm for minimizing periodic preventive maintenance cost for series-parallel systems subjected to reliability considerations. Periera et al. [73] used PSO algorithm for preventive maintenance scheduling, so that the cost and system unavailability were minimized. Mansour [74] demonstrated the utility of GA in solving periodic maintenance scheduling problem, in such a way that total variance in workforce level, and maintenance costs could be minimized.

1.4.3 Studies on Joint Preventive Maintenance Scheduling and Spare Parts Inventory Control

Classical inventory model developed by Harris [1] in 1913, provided a simple formulation for the EOQ that would minimize the total inventory cost (inventory holding, ordering and backordering). The model had many simplifying assumptions like demand for a product is known a-priori, demand is fixed and delivery is instantaneous. Subsequently, a lot of researchers developed it further to suit various real-life situations. Jaber [75] presented some of the non-classical approaches to inventory management in 2009.

Mathematical theory of reliability was developed by Barlow and Proschan [76] in 1965. This theory had not only been applied to various diverse fields in engineering and technology, but also a lot of investigation had been done on applicability of mathematical theory of reliability to decision making in the field of maintenance. Fundamental and theoretical work in the areas of reliability were detailed by Pham [77]. Nakagawa [57] described many maintenance policies that are applicable in modern industrial environment. Reliability and optimal maintenance had been discussed by Wang and Pham [58] in 2006.

Early attempts to apply classical inventory analysis to spare part inventory could be seen in the work by Flowers and O'Neill [78] in 1978. They utilized ABC analysis for spare part inventory of an automated manufacturing facility. Kaio and Osaki [79] developed optimum ordering policies with lead time for preventive maintenance situations in 1978. Further in 1981, Osaki et al. [80] summarized optimal ordering policies as available in contemporary literature. In the same year, Yamada and Osaki [81] investigated into possible optimum replacement polices for system, which might have basically two types of components, viz., non-essential and essential. They had developed initial provisioning policy for non-essential components.

In 1986, Acharya et al. [82] developed a policy for joint optimization of block-replacement and spares. They found that the jointly optimal preventive replacement interval is appreciably different from the corresponding optimal preventive replacement interval, where only the replacement related costs were considered. Park and Park [83] in 1986, proposed ordering policies for maintenance of spares, wherein the procurement lead time had a finite non-negligible value. Investigation into joint optimization of maintenance and inventory for age replacement and spare ordering decisions for a system comprising of one machine subject to random failure, with only one spare machine in stock was done by Armstrong and Atkins [84] in 1998.

Yoo et al. [85] developed an expected cost model for joint spare stocking and block replacement policy using the renewal process, where a group of identical machines was simultaneously put to service. Continuously monitored deteriorating systems were modeled utilizing Monte Carlo simulation by Barata et al. [86]. The problem of joint optimization of preventive maintenance and spare-provisioning policy for system components subject to wear-out failures was investigated by Brezavscek and Hudoklin [87] in 2003. The expected total cost of system maintenance per unit time was taken as the objective function, and the preventive replacement interval and the maximal inventory level were chosen as the decision variables. Ghodrati and Kumar [88] developed the methods for forecasting requirement of maintenance spares, based on technical characteristics and the system-operating environment.

Generalized spare ordering policies for a single unit system with age-dependent minimal repair and random lead time was investigated by Chien [89]. It was seen that that there could be a unique and finite optimum under certain conditions. Ilgin and Tunali [90] utilized GAs for joint optimization of spare parts and maintenance policies for an automotive factory. Gharbi et al. [91] developed model that could determine optimal safety stocks and preventive maintenance periods for unreliable manufacturing systems in 2007. A numerical procedure was suggested for obtaining solutions of the model.

A joint strategy of stock provision and condition-based preventive maintenance was suggested by Xie and Wang [92] in 2008. They combined continuous review ordering policy with inspection for condition-based preventive maintenance and GAs were utilized for searching the optimal joint strategy, which could minimize the total costs associated with maintenance and inventory. Hu et al. [93] investigated feasibility of joint optimization of age replacement and spare ordering policy by integrating discrete event simulation with the GAs. The sufficient and necessary conditions of the existence and uniqueness of the minimum in the joint models of block-replacement and spare inventory with random-leadtime were investigated by Huang et al. [94]. Bevilacqua et al. [95] studied spare parts inventory control and concluded that Poisson distribution could be better suited than normal distribution for modeling the demand for slow-moving items.

Brezavscek and Hudoklin [96] investigated the suitability of various types of failure probability functions, viz., exponential, normal, Weibull and Gamma, for planning the inventory of spare components in 2010. Rausch and Liao [97] modeled production and spare part inventory control for condition-based maintenance. They developed a heuristic two-step approach, for assessing the optimal number of spare parts, along with the preventive maintenance threshold. The failure process was modeled as a non-homogeneous Poisson process, and the cost elements towards ordering, shortage, repair, replacement cost, and salvage value, were considered in the the optimal spare ordering model by Chen and Chien [98] in 2010. A comprehensive review of spare parts management was carried out by Boylan and Syntetos [99] in the same year.

Xu et al. [100] utilized numerical methods (in Matlab) to obtain solution to the problem of joint optimization of spare stock and age-based replacement policy. Louit et al. [101] followed reliability approach to develop optimization models for critical spare part inventories. They focused attention towards reducing the cost while simultaneously increasing availability of the machine. Gamma distribution was utilized for modeling material degradation, and collaborative optimization of maintenance and spare ordering was investigated for such continuously degrading systems by Zhou et al. [102]. Basten et al. [103] modeled the joint problem of level of repair-cum spare parts stocking and found out that the lower overall costs could be achieved by combining the two objectives. Nourelfath and Chatelet [104] developed integrated lot-sizing and preventive maintenance strategy that could minimize the sum of maintenance, inventory and production costs, while simultaneously satisfying the demand. A model that could determine the maximum availability and preventive maintenance action of a series-parallel system, subject to budget constraint, was developed by Nourelfath et al. [105]. Reliability-based investigations into optimal maintenance interval and spare part inventory for the system experiencing aging was done by Kurnaiti et al. [106], who concluded that failure data collected from the field could be useful in developing optimum maintenance policies.

In recent times, Chen et al. [107] developed an analytical framework, which could minimize the undiscounted long-run average cost under availability constraint for joint maintenance and spare parts provisioning. The model developed by Liu et al. [108] could suggest spare inventory and maintenance strategy for multi-failure states using stochastic dynamic programming methods. Horenbeek et al. [109] studied the effect of variation in quality of spare parts on joint policy of maintenance and spare parts inventory. Three new metrics, viz., aggregate fill rate, average downtime and expected total number of long downs in joint modeling of reliability and inventory problems were suggested by Selcuk and Agrail [110]. Xie et al. [111] considered redundancy allocation and spare parts provisioning simultaneously in maximizing the system's operational availability. Xiao and Peng [112] utilized a GA to evaluate the system's availability of multi-state elements in series-parallel systems. The effects of external factors like environment, maintenance policy, skill of operator etc. on the reliability and consequently, the requirement of spare parts was investigated by Barabadi et al. [113].

1.5 Motivation

The motivation behind the present study is presented below.

1.5.1 Problems Related to Inventory Control

Different parameters of inventory models had been modeled using the concept of fuzzy sets. The performance of those models were dependent on the shape and size of membership function distributions, which were not optimized in most of the studies. Thus, there is a chance of further improvement of those models.

Fuzzy economic order quantity models without and with backordering, both for the cases of fixed and variable demands could possibly be developed using the concept of fuzzy sets, formulated as an optimization problem and solved using the optimization tools like GA and PSO algorithm. It could be possible to determine the size of economic order quantity that would keep the total inventory cost within the allotted budget level.

1.5.2 Problems Related to Preventive Maintenance Scheduling

Mean cost rate of maintenance of a machine over its useful service life depends on many variables and it might be possible to optimize the same by using either analytical methods or semi-numerical algorithms, where the failure time distribution is a two-parameters Weibull distribution. However, in real practice, the failure time distribution could follow a more complicated distribution. Moreover, the failure distributions might be different for various machines. On top of the above, a large machine may have thousands of components, which would make the analysis an extremely complex one. Therefore, it is felt that investigations could be done for real situations and models be built that would closely describe the above fact. Further, as the objective function could not only become more complex but also change from machine to machine, non-conventional optimization tools like GA and PSO algorithm could give better results.

1.5.3 Problems Related to Joint Preventive Maintenance Scheduling and Spare Parts Inventory Control

The ability to predict the occurrence of failure is central to the development of preventive maintenance models. After a reasonable and fairly accurate evaluation of the number of likely failures in a given time interval has been carried out, the next activity would be to evaluate the requirement of maintenance spares. Thereafter, the cost towards maintenance and spares parts could be combined in a suitable way and further analysis might be carried out for the optimization of total cost. However, the joint cost models so developed are likely to have complex mathematical formulations and therefore, it is not possible to solve the same analytically except for a few limited situations or until unless, some extra simplifying assumptions are made. Quiet frequently, researches have developed numerical procedures and algorithms for obtaining solutions of the models.

Further, it has also been observed that failure of a working machine may follow various types of failure probability distribution functions. Hence, optimization procedures developed for one type of failure probability distribution may not yield correct results, if these are applied to another machine, since the basic failure probability distribution is likely to be different for different machines. Therefore, it is felt that better results could be obtained, if non-conventional optimization tools like GA and PSO algorithm are utilized instead, which could provide optimal solutions irrespective of the complexity of the objective functions.

1.6 Aims and Objectives

The aims and objectives of this study were set as follows:

1. Determine optimal order quantity in a fixed demand inventory model under uncertainties arising due to fuzziness in various cost elements like inventory holding cost, cost towards ordering of inventory and backordering cost, while simultaneously keeping the total cost within a predefined limit.

2. Optimize the above problem using genetic algorithms and particle swarm optimization algorithm and compare their performances, for two different types of membership function distributions, namely triangular and Gaussian ones.

3. Obtain optimal order quantity in a variable demand inventory model for minimizing inventory cost after treating the holding and ordering costs and demand as independent fuzzy variables, which would minimize the fuzzy expected value of the total cost, so that the credibility of the total cost not exceeding a certain budget level is maximized.

4. Optimize the variable demand inventory control model using genetic algorithms and particle swarm optimization algorithm, for triangular and Gaussian membership function distributions, and suggest suitable managerial inputs for an industry.

5. Ascertain optimum maintenance schedules for three types of sequential imperfect preventive maintenance models, viz., age reduction model,

hazard rate model and hybrid model using GA and PSO algorithm, and validate the results with that of the published literature, vis-a-vis results obtained through semi-analytical/semi-numerical methods.

6. Utilize the developed methods to analyze and suggest the optimum preventive maintenance schedule in some industrial scenarios.

7. Carry out joint optimization of preventive maintenance and spare parts inventory model using the GA and PSO algorithm, and ascertain the degree to which the results obtained by the above two non-conventional optimizers are in agreement with those obtained for the similar models through semi-numerical method.

8. Apply the procedure so developed for joint optimization of preventive maintenance and spare parts inventory model, and suggest optimum time schedules for some complex machineries of the industry.

1.7 Contributions Made by the Scholar

1. In real-life situations, the decision variables influencing Economic Order Quantity (EOQ) in an inventory model are fuzzy in nature and vary in unpredictable manner. EOQ models that could keep the total cost towards procurement, storage of inventory in dynamically varying and uncertain situations within some preallocated budget were developed, and solutions to the same were obtained by using a GA and PSO algorithm. Real data from two different industries, viz., fabrication and painting, were collected and tested on the developed model. It was

observed that the models could indeed provide economic solutions, in uncertain situations.

2. Shop-floor managers invariably need to ensure that the critical machines provide uninterrupted service by ensuring timely preventive maintenance. Preventive maintenance schedules that could minimize the expected cost rate and overall expenditure towards maintenance for age reduction model, hazard rate model and hybrid model were determined utilizing the GAs and PSO algorithms. A considerable saving was observed, when the procedures were applied to an industrial problem for a fleet of railway locomotives.

3. Planning for maintenance schedules and management of associated inventory of essential spare parts go hand-in-hand. GAs and PSO algorithms were used to find optimum maintenance schedules for the joint preventive maintenance and spare parts inventory situations. Even though the objective functions of the joint model are mathematically complex, the revised time schedule suggested by the joint model for an electric overhead traveling crane, showed the possibility of a lot of savings in total expenditure towards maintenance.

1.8 Organization of the Thesis

The thesis is organized as follows: The tools and techniques used in this study are discussed in chapter 2. Chapter 3 discusses the models of inventory control in uncertain environments. Preventive maintenance, especially sequential imperfect preventive maintenance is studied in chapter 4. Chapter 5 deals with the study of the joint model of preventive maintenance and inventory control. Some concluding remarks are made and the scope for future studies are suggested in chapter 6.

1.9 Summary

This chapter presents a review of contemporary research on the fields of inventory, maintenance and joint inventory-maintenance models. Gaps in the literature are ascertained, which form the motivation behind this study. The aims and objectives of this study along with the new contributions made in these fields are also presented. This chapter ends with an organization of the thesis.