CHAPTER 2

LITERATURE REVIEW

This chapter presents literature reviews of the ergonomics background on industrial noise and industrial noise hazard prevention involving three approaches of noise controls. The engineering controls and the use of hearing protective devices are widely discussed by researchers, while the administrative controls are rarely considered. Other literature reviews include the genetic algorithms (GAs), Decision Support Systems (DSS) and the auditory warning systems in industrial workplaces.

2.1 Industrial Noise

This section presents the review on the background of fundamentals and physical properties of sound (or noise). The measurements of noise level are described. The permissible noise exposure limit for every worker, which is usually recommended to be equal to an 8-hour time-weighted average (TWA) of 90 dB*A*, is defined.

2.1.1 Measures of Noise Levels

Three basic measures of sound: sound power, sound intensity, and sound pressure are explained in this section. This section also describes how to measure the combined noise level at specific locations.

- *Sound Power*

Sound power is an acoustic power radiated by a given source in all directions. It is measured in watts, W. The sound power of a noise source is conventionally expressed as *P*.

- *Sound Intensity*

Sound intensity is an acoustic power per unit area. Its unit is watts per square meter (W/m^2). Given the acoustic power *P*, sound intensity *I* at distance *d* (in meters) from acoustic center of the noise to imaginary spherical surface can be determined from

$$I = \frac{P}{4\pi d^2} \tag{2.1}$$

- *Sound Pressure*

A sound wave is caused by the vibrations of a sound-generation source. The positions of the wave above or below the midline represent the amount of above-normal or below-normal air pressure at that point. The greater the deviation above or below normal of the air pressure, the louder the sound level will be. Because of the wide range of sound pressures to which the ear can respond, it has been decided to adopt logarithmic scales for the representing sound quantities. As a result, sound powers, intensities, and pressures are commonly stated in term of the logarithm of the ratio of measured quantity to an appropriate quantity. Whenever the magnitude of a sound quantity is given in this logarithm form, it is said to be a level in decibels (dB) above or below a zero reference level that is determined by a reference quantity. The following equations show the logarithm form of sound quantities:

Sound power level	L_P	=	$10 \log_{10} (P/P_o)$	dB,	(2.2)
Sound intensity level	L_I	=	$10 \log_{10} (I/I_o)$	dB,	(2.3)
Sound pressure level	L	=	$10 \log_{10} (p/p_o)$	dB,	(2.4)

where P_o, I_o, and p_o = 10^{-12} W, 10^{-12} W/m^2, and 20 μN/m^2, respectively.

By equating L and L_I and simplifying the equation, it can be determined that the difference between the two quantities is not significant and can be neglected (Beranek, 1992). Thus $L \approx L_I$, or

$$L = 10 \log_{10} (I/I_o) \qquad (2.5)$$

From equation (2.1) and (2.5), the practitioner is also allowed to convert from sound power to sound intensity to sound level, or vice versa.

The American National Standard Institute (ANSI) requires that three different weighting networks (A, B, and C) be built into sound measurement instruments. It has become conventional to write the letter A, B, or C after dB to indicate the type of weight network that the instrument uses. Among them, the A scale has been selected as the appropriate measure of environmental noise by the U.S. Environmental Protection Agency perhaps because it comes closest to approximating the response characteristics of human hearing.

When there are multiple noise sources in the facility, the combined noise level at worker location j, $\bar{L}_j$ (dBA), can be computed. Letting L_{ab} be ambient noise level (dBA), L_t be noise level generated by noise source t (dBA, measured at 1-m distance), q be number of noise sources, n be number of worker locations, and d_{jt} be Euclidean distance between worker location j and noise source t, the combined noise level $\bar{L}_j$ at location j can be generalized and written as

$$\bar{L}_j = 10\log\left[10^{\left(\frac{L_{ab}-120}{10}\right)} + \sum_{t=1}^{q} \frac{10^{\left(\frac{L_t-120}{10}\right)}}{d_{jt}^2}\right] + 120 \qquad j = 1,\ldots, n. \qquad (2.6)$$

2.1.2 Permissible Noise Exposure Limits

Generally, there are machines operating in a workplace making loud noise. Since it may not be possible to design a quiet machine, we can limit the exposure time of workers who operate in noise hazardous conditions. The Occupational Safety and Health Administration (OSHA), has established permissible noise exposure for industrial workers (OSHA, 1983). The permissible levels depend on the exposure durations shown in Table 2.1. If the worker is exposed to loud noise levels, the allowable duration of exposure will be short. Moreover, exposure to noise levels below 80 dBA is not considered as hazardous and does not require a time limit. In addition, exposure above 115 dBA is not permitted regardless of duration.

There are two measures of permissible noise exposures. They are (1) a daily noise dose, and (2) an 8-hour time-weight average sound level. Normally, as a worker has to work in several work areas and is exposed to different noise levels during an 8-hour workday, it is necessary to measure the daily exposure to these noise levels. If the worker's daily exposure exceeds the permissible level, the noise control must be implemented.

Table 2.1 Permissible Noise Exposures (OSHA, 1983)

Noise Level (dB*A*)	Permissible Time (Hour)
80	32
85	16
90	8
95	4
100	2
105	1
110	0.5
115	0.25

- *Daily Noise Dose*

It is known that exposure to any noise level at or above 80 dB*A* causes the worker to receive a partial dose of noise and exposure to noise levels below 80 dB*A* is negligible to calculate noise dose. The daily noise dose then is equal to the sum of the partial doses. A partial dose is defined as the ratio of time actually spent at noise level to the maximum permissible time at noise level (determined from Table 2.1). By knowing the noise level of a given work area and the exposure duration, the daily noise dose D_T (in percent) can be calculated from

$$D_T = 12.5 \sum_{j=1}^{n} C_j \left[2^{\frac{\bar{L}_j - 90}{5}} \right] \tag{2.7}$$

where C_j is the length of time (in hours) that the worker operates at worker location j, and $\bar{L}_j$ is the combined noise level (dB*A*) at worker location j. A noise dose of 100 percent is designated as the permissible noise exposure level.

- *8-hour Time-weighted Average Sound Level*

In order to express the noise exposure level in dB*A*, the daily noise dose can be converted into an 8-hour time-weighted average (TWA) sound level. The TWA is the equivalent sound level (in dB*A*) that would produce a given noise dose if a worker were continuously exposed to that sound level over an 8-hour workday. The formula for calculating TWA is given below.

$$\text{TWA} = 16.61 \left[\log_{10} \left\{ \sum_{j=1}^{n} \frac{C_j}{8} \left(2^{\frac{\bar{L}_j - 90}{5}} \right) \right\} \right] + 90 \tag{2.8}$$

It can be proved that a noise dose of 100 percent is equivalent to a TWA of 90 dB*A*. Thus the 90-dB*A* TWA is the permissible noise exposure level as well.

2.2 Industrial Noise Hazard Prevention

Noise-induced hearing loss is one of the most common occupational diseases and the second most self-reported occupational illness or injury (NIOSH, 1998). Exposure to high noise levels is a leading cause of hearing loss and may also result in other harmful health effects. A major cause that contributes to this problem is a lack of effective noise hazard prevention programs in the workplace.

An effective noise hazard prevention program requires a workplace noise control. Three noise control approaches are generally recommended: (1) engineering approach, (2) administrative approach, and (3) the use of hearing protection devices (HPDs). The details of engineering controls can be found in Harris (1979), Beranek and Ver (1992), Cheremisinoff (1993), Ridley (1994), Wilson (1994), and Bies and Hansen (1996). Topics such as a development of quieter machines, noise reduction methods, noise absorption materials, and process change for noise reduction are also discussed in the literature (Richards, 1981; Vajpayee *et al.,* 1981; Docherty and Corlett, 1983; Cops, 1985; Li and Halliwell, 1985; Baek and Elliott, 1995; Bahrami *et al.*, 1998; Lee and Ng, 1998; Sorainen and Kokkola, 2000; Bilawchuk and Fyfe, 2003).

For the administrative approach, job rotation is perhaps the most recommended method to reduce the worker's exposure to loud noise. Nanthavanij and Yenradee (1999) developed a *minimax* work assignment model (i.e., a job rotation model) to determine an optimal set of work assignments for workers so that the maximum daily noise exposure that any worker receives is minimized. For large-sized job rotation problems, a genetic algorithm was developed to determine near-optimal *minimax* work assignments (Nanthavanij and Kullpattaranirun, 2001; Kullpattaranirun and Nanthavanij, 2005). Yaoyuenyong and Nanthavanij (2003) also developed a simple heuristic for solving large job rotation problems. When noise levels are excessive, Nanthavanij and Yenradee (2000) recommended that the number of workers be greater than the number of machines/workstations where workers must be allocated. A mathematical model was developed to determine the minimum number of workers for working in noisy work areas so that their daily noise exposures do not exceed the permissible limit.

Various types of HPD and their properties have been widely discussed in Harris (1979), Beranek and Ver (1992), Cheremisinoff (1993), Ridley (1994), and Wilson (1994). In addition, research studies on the development and testing of effective HPDs were carried out by Behar and Kunov (1999), Crabtree and Behar (2000), Birch *et al.* (2003), and Buchweiller *et al.* (2003). Resistance to using HPDs by workers was also studied by Feeney (1986).

In situations where the noise level exceeds 90 dB*A*, a noise conservation program is required (OSHA, 1983). According to the OSHA's hierarchy of noise control, engineering controls are to be considered first. If they are not feasible or insufficient, administrative controls such as job rotation should be considered next. The use of HPDs is to be used as the last resort of noise reduction. HPDs should be used to assist, not to replace, engineering and administrative controls. However, employers usually provide HPDs (earplugs, earmuffs, etc.) to workers for noise protection without attempting to apply engineering and administrative controls. The main reasons for not considering them are a large capital investment that is normally required for engineering controls and the difficulty in implementing engineering and administrative controls.

Sanders and McCormick (1993) recommended that three noise control approaches should be implemented in noise control strategy as a combination of noise controls so as to achieve the desired level of abatement. Therefore, to find a proper combination of noise controls is a difficult task, especially when requirements such as allocated budget and permissible noise level need to be concurrently considered. Furthermore, administrative controls (e.g. job rotation) may require the knowledge in mathematics or operations research; therefore, safety practitioners do not intend to choose them for noise control.

2.3 Genetic Algorithms

Many problems in the industrial engineering field cannot be optimally solved by an optimization approach. Among various meta-heuristic techniques, genetic algorithms (GAs) which were developed by Holland (1975) have been well adopted by several researchers to find good solutions for global and hard-to-solve optimization problems. Goldberg (1989) has summarized the differences of genetic algorithms from the conventional optimization approach and search procedures in many aspects as follows:

- Genetic algorithms work with a coding of solution set instead of the solutions themselves.
- Genetic algorithms search from a population of solutions instead of a single solution.
- Genetic algorithms use fitness function instead of derivative or other auxiliary knowledge.
- Genetic algorithms use probabilistic transition rules instead of deterministic rules.

The general GA procedure is described in the following steps.

Step 0: Randomly generate the initial solution.

Step 1: Evaluate the chromosomes by calculating the evaluation function. Then, update the best solution.

Step 2: Perform the selection as follows.

- Calculate the selection probability.
- According to crossover probability, select pairs of strings from the current population to perform crossover and mutation

Step 3: Apply the crossover operation to each pair selected from step 2.

Step 4: According to mutation probability, apply the mutation operation to each string generated by crossover.

Step 5: Check for the stopping condition. If stopping condition is not satisfied, return to step 1. Otherwise stop procedure.

Randy and Sue (1998) presented some advantages of GA as follows:

- Optimizes both continuous and discrete parameters.
- Does not require derivative information.
- Simultaneously searches from a wide sampling of cost surface.
- Deals with a large number of parameters.
- Is well suited for parallel computers.
- Optimizes parameters with extremely complex cost surfaces; they can jump out of a local minimum.
- Provides a list of optimal parameters, not just a single solution.
- May encode the parameters so that the optimization is done with the encoded parameters.
- Work with numerically generated data, experimental data, or analytical function.

Genetic algorithms (GAs) have served as an alternative approach to a wide range of combinatorial optimization problems, such as knapsack problems (Olsen, 1994), quadratic assignment problems (Tate and Smith, 1995), traveling salesman problems (Goldberg and Lingle, 1985; Cheng and Gen, 1994; Yang, 1997), and machine-part cell formation problems (Mak and Wong, 2000; Brown and Sumichrast, 2001; Chu and Tsai, 2001). When applying GA, heuristic algorithms that are specific for the given problems are usually developed. For example, Cheng and Gen (1994) developed the greedy selection crossover (GSX) to improve the speed and accuracy of GA when solving traveling salesman problems. For similar problems, Yang (1997) developed another crossover operator based on the operators developed by Grefenstetts *et al.* (1985) and Starkweather *et al.* (1991).

For the *balanced* work assignment problem, Nanthavanij and Kullpattaranirun (2001) introduced a genetic algorithm to determine near-optimal *minimax* work assignments which prevent workers from receiving high noise levels. A heuristic genetic algorithm for the *minimax* work assignment problem that improves the computation time and quality of solution was later developed by Kullpattaranirun and Nanthavanij (2005). Readers should note that those two GAs are unconstrained GAs; thus, the resulting *minimax* noise exposure may exceed the permissible level.

The GA is also widely used to solve linear/nonlinear *zero-one* programming problems as well as linear/nonlinear integer programming problems. Yokata *et al.* (1995 and 1996a), formulated an optimal design problem of systems reliability as the *zero-one* nonlinear programming problem with interval coefficients and solved it using the GA.

Recently, the GA has been applied to solve manufacturing problems such as scheduling problems in flexible manufacturing systems, sequencing problems in mixed model assembly lines and in non-manufacturing problems such as fair bandwidth allocation and multi-objective land use planning problems.

Soukhal and Martineau (2003) used GA to solve a scheduling problem in a flexible manufacturing system. They considered a flowshop robotic cell that processes several jobs. An integer programming model to determine the sequence of jobs that minimizes the makespan criterion is presented. The proposed GA can successfully solve large-sized problems. The computational experiments were also done in order to compare the makespan returned by the GA to a lower bound**.**

A genetic algorithm for mixed model assembly lines was proposed by Ponnambalam *et al.* (2003). Mixed model assembly lines are a type of production line where a variety of product models similar in product characteristics are assembled. The effective utilization of these lines requires that a schedule for assembling the different products be determined. The investigation of performance of genetic algorithms for sequencing problems in mixed model assembly lines was done by the comparison between a existing heuristic and the proposed GA. Three practically important objectives in this research were minimizing total utility work keeping a constant rate of part-usage, minimizing the variability in parts usage, and minimizing total setup cost.

Lee *et al.* (2004) presented the fair bandwidth allocation which is an important issue in the multicast network to serve each multicast traffic at a fair rate commensurate with the receiver's capabilities and the capacity of the path of the traffic. A lexicographically fair bandwidth layer allocation problem was formulated as a nonlinear integer programming problem. A nonincreasing convex function of the bandwidth layers of the virtual sessions was employed to maximize the bandwidth of each virtual session from the smallest. To solve the fairness problem a genetic algorithm was developed based on the fitness function, ranking selection and the shift crossover. Outstanding performance was obtained by the proposed GA in various multicast networks. The effectiveness of the GA became more powerful as the network size increased.

Stewart *et al.* (2004) described a class of spatial planning problems in which different land uses have to be allocated across a geographical region, subject to a variety of constraints and conflicting management objectives. The problem was formulated as a goal programming, which leads however to a difficult nonlinear combinatorial optimization problem. Then a special purpose genetic algorithm was developed for the solution of this problem, and was extensively tested numerically. The model and algorithm was then applied to a specific land use planning problem in The Netherlands. The ultimate goal was to utilize the algorithm in a complete land use planning decision support system.

The GA was also used to determine solutions for various optimization problems in recent research studies: Coit and Smith (1996); Yokota *et al.*, (1996b, 1997, 1998); Zheng *et al.* (1998); Tanguchi and Yokota (1999); Chen and Fischer (2000); Ji *et al.* (2001); Deo *et al.* (2002); Tseng and Din (2002).

2.4 Decision Support Systems in Industrial Engineering

2.4.1 Definitions and Characteristics

Decision Support Systems (DSS) have become a popular tool to solve the problems. The definitions of DSS were stated by the following literatures.

- Little (1970) defined DSS as a "model-based set of procedures for process data and judgments to assist a manager in his decision making." To be successful, such a system must be simple, robust, easy to control, adaptive, complete on important issues, and easy to communicate with.
- Moore and Chang (1980) defined DSS as extendible systems capable of supporting ad hoc data analysis and decision modeling, oriented toward future planning, and used at irregular, unplanned intervals.
- Bonczek *et al.* (1980) defined a DSS as a computer-based system consisting of three interacting components: a language system, a knowledge system, and a problem-processing system.

Er (1988) described DSS in three aspects – namely, Decision, Support and System. The word decision in DSS implies problem solving, in addition, problem solving implies the use of knowledge in solving the problem. The support aspect of DSS implies the use of computer and software technologies to support user during the decision making process. The word system in DSS implies a system of man-machine interactions and its design and implementation.

Since there is obviously no agreement on standard characteristics and capabilities of DSS, Turban and Aronson (1998) therefore described an ideal set of them as follows:

- A DSS provides support for decision makers mainly in semistructured and unstructured situations by bringing together human judgement and computerized information. Such problems cannot be solved conveniently by other computerized systems or by standard quantitative methods or tools.
- Support is provided for various managerial levels, ranking from top executives to line managers.
- Support is provided to individuals as well as to groups. Less structured problems often require the involvement of several individuals from different departments and organizational levels.
- A DSS provides support to several interdependent and/or sequential decisions.
- A DSS supports all phases of the decision-making process: intelligence, design, choice, and implementation.
- A DSS is adaptive over time. The decision maker should be reactive, able to confront changing conditions quickly, and adapt the DSS to meet these changes. A DSS is flexible; therefore, users can add, delete, combine, change, or rearrange basic elements.

- Users must feel at home with a DSS. User friendliness, strong graphic capabilities, and an English-like interactive human-machine interface can significantly increase the effectiveness of a DSS.
- A DSS attempts to improve the effectiveness of decision making (accuracy, timeliness, quality), rather than its efficiency (cost) of making decisions.
- The decision maker has complete control over all steps of the decision-making process in solving a problem. A DSS specifically aims to support and not to replace the decision maker.
- A DSS usually utilizes models for analyzing decision-making situations. The modeling capability enables experimenting with different strategies under different configurations.

Holsapple and Whinston (1996) also suggested the characteristics of DSS as follows:

- A DSS includes a body of knowledge that describes some aspects of the decision-maker's world, that specifies how to accomplish various tasks, that indicates what conclusions are valid in various circumstances, and so on.
- A DSS has an ability to acquire and maintain descriptive knowledge (i.e., record keeping) and other kinds of knowledge as well (i.e., procedure keeping, rule keeping, etc.)
- A DSS has an ability to present knowledge on an ad hoc basis in various customized ways.
- A DSS has an ability to select any desired subset of stored knowledge for either presentation or deriving new knowledge in the course of problem recognition and/or problem solving.
- A DSS can interact directly with a decision maker or a participant in decision making in such a way that the user has a flexible choice and sequence of knowledge-management activities.

2.4.2 Applications of DSS in Industrial Engineering Problem

DSS has been applied to many problems in various areas. In this review, the author mainly focuses on the DSS applications in the area of engineering problems, such as production management and job scheduling.

"Decision Support System is an interactive computerized system that is designed for easy use by both the practicing manager and the industrial engineer/management scientist" (Turban, 1983). The DSS concept has been widely applied to engineering environments and management systems. Hanss (1984) also discussed the use of DSS in engineering management. Parker *et al.* (1994) developed DSS for scheduling technical personnel. The DSS approach to problem solving in an engineering environment and the review were discussed by Elfner (1988). For production management, Biswas *et al*. (1988) designed a DSS for production control. They developed the expert decision support system which can emulate a consultant and aid management in troubleshooting the manufacturing processes. The expert system was designed for diagnosing production control problems to determine the general cause or set of causes that best match the observed symptoms described by the user. By using various techniques such as simulation, regression, operation research models and heuristics, the expert system can recommend the actions to eliminate the causes or alleviate the effects of production control problems. In 1996, Grabot *et al*. developed DSS to handle production activity control. Owing to the imprecision and uncertainty of the information, fuzzy logic and theory of possibility are required. The DSS can determine the minimization of the resource use, of the overloads of direct costs, and so on. Wong *et al*. (1999) designed DSS to assist a jewellery manufacturer to make decisions in various areas of operation, including price quotation, sales analysis, and materials requirement planning. Buehlmann *et al*. (2000) designed a spreadsheet-based DSS known as Lignum Optimizer which allows particle board plant managers to find the lowest cost solution for their production requirements. The DSS was developed to cope with allocating production resources and combining various raw materials to meet production goals. This DSS allows users to evaluate different scenarios relating to their production and thus to make the best decisions possible under existing situations.

In scheduling problems, various approaches in DSS are introduced. Kassicieh *et al*. (1986) developed the DSS for conducting the academic scheduling. A decision support system based on a simulation model of the detailed scheduling activities in a tractor manufacturing company was designed by Ozdemirel and Satir (1987). The system generates a number of reports utilized in the decision making process (planning and control) regarding various aspects of detail scheduling. Schniederjans and Carpenter (1996) developed a heuristic-based DSS for employee job scheduling. Job scheduling is determined according to the DSS model and it is only a preliminary scheduling to permit the user to review the schedule for the final approval. It was observed that the proposed DSS software yielded the job schedules without violating work rules or ergonomic limitation while about ten percent of the schedules generated manually resulted in a violation of work rules and ergonomic limitation.

A number of researches on DSS for logistics management were developed. Some researchers used another optimization model to deal with distribution planning in order to solve an empty container distribution planning problem for a shipping company (Shen and Khoong, 1995). Korpela and Tuominen (1996) developed a decision support system based on the analytic hierarchy process which forms the basis for a systematic and flexible strategic issues management process. They presented an approach to logistics strategic management where a periodic strategic planning process and a continuous strategic issues management process are integrated. The proposed DSS is based on the principles of the analytic hierarchy process where a complex, multicriteria problem is broken down into a hierarchy. The proposed DSS first estimates the impact of the identified strategic issues on each key corporate an logistic objective of the company and then determines the most effective actions to deal with the strategic issues with the highest and either positive or negative impact on the company.

Wang *et al*. (1991) designed a DSS, which applied the fuzzy set method for robot selection. Abdel-malek and Resare (2000) developed analytical models, algorithms and DSS to aid decision makers in the selection of machining/assembly cell components from the milieu available in the marketplace. The DSS can recommend the machining that maximizes the cell’s performance subject to various operational and budget constraints. Klapka and Pinos (2002) presented DSS to carry out multicriteria selection of hundreds of projects simultaneously, with tens of criterion functions. This system also enables the use of dialogues to support both the improvement of the solution of ill-defined selection problems and the flexible changes of solution in case of change to the problem parameters. Ntuen *et al*. (1995) presented a prototype knowledge-based training selection. In manufacturing training, the problem of selecting employees for training is time consuming and belongs to a special class of multiattribute decision making. The developed expert system can identify and weight trainability factors and advise managers on the employee trainability level. The proposed system evaluates the user subjective input and produces some fuzzy ranking to assist management in making decisions.

A number of DSS applications were also developed to deal with human resource management, for example, productivity improvement (Young, 1989) and performance analysis (Ntuen *et al.,* 1994). A computer-based system for risk management was presented by Peckham *et al.* (1988). The DSS for risk assessment was also developed by Gheorghe *et al.* (2000). Various DSS in engineering fields have been discussed in Padillo *et al.,* 1995; Chaudhry *et al.,* 1996; Kim and Lee, 1997; Kengpol, 2004; Chien and Deng, 2004.

2.5 Auditory Warning System in Industrial Workplace

Auditory warnings are widely used in a variety of work environments. Edworthy and Hards (1999) stated that "Auditory warnings act as a vital corollary to visual warnings and cues and can be particularly useful when people are working under conditions of high workload, especially high visual workload, and/or when the operator has high movement to various areas, or visual conditions are bad."

The regulations of national safety organizations in many countries force employers to provide warning systems to alert workers to the unsafe working environment. When the warning system is installed in the workplace, safety practitioners or engineers must consider the effectiveness of that system. Normally, alarm devices may generate auditory signals, visual signals, or both types of signals when hazardous or dangerous situations are detected. Among them, the use of auditory signals seems to be a better choice for industrial facilities than the use of other types of signals because workers can perceive (hear) the signals even if they are not watching or are working in areas where they cannot see the alarm devices. Edworthy and Hards (1999) also reported that the number of studies on auditory warnings is relatively higher than that on visual warnings. Design guidelines and recommendations related to auditory warning systems can be found in several ergonomics and safety publications (Kantowitz and Sorkin, 1983; Sanders and McCormick, 1993; Stanton and Edworthy, 1998; Edworthy and Hards, 1999). The characteristics of the auditory signals such as intensity, frequency, duration, type, etc., have been discussed in depth in the literature (Deatherage, 1972; Wilkins and Martin, 1987; Sanders and McCormick, 1993). Literature on the learning and retention of warnings can also be found in Patterson (1982), Monthahan *et al.* (1993), and Edworthy and Merredith (1997). The International Organization for Standardization (ISO) has also published international standards on auditory danger signals for workplaces. They are: (1) ISO 7731:1986 – Danger signals for work places – Auditory danger signals, and (2) ISO 11429:1996 – Ergonomics – System of auditory and visual danger and information signals.

To comply with the safety regulations and standards, employers are required to install alarm devices in their facilities to alert workers of hazardous and/or dangerous situations. Examples of guidelines for the sufficient detection of auditory signals are as follows:

1. In quiet work environments, an auditory signal about 40-50 dB*A* above the absolute threshold normally is sufficient to be detected (Sanders and McCormick, 1993).
2. In noisy work environments, a minimum level of 15 dB*A* above the masked threshold to ensure detect ability and a maximum level of 25 dB*A* above the masked threshold to guard against annoyance and disruption are recommended (Patterson, 1982).

The International Standard, ISO 7731, states that "the auditory signal is clearly audible if the signal sound level exceeds the level of ambient noise by at least 15 dB*A*." For workers with normal hearing or mild hearing loss, the signal sound level (measured at the worker's ear) shall be not less than 65 dB*A* to ensure its audibility (ISO 7731:1986).

Nanthavanij and Yenradee (1994) and Nanthavanij (1995) considered the number of alarm devices, location, and the signal sound level as important factors that have a significant effect on the audibility of the auditory warning system. They presented an analytical method for predicting the location of an alarm device based on the ambient noise level, the location and sound level of other sound generating sources, and the location of workers in the workplace. The method, however, is limited to only single alarm location problems. Later, Nanthavanij and Yenradee (1999) proposed an analytical method for predicting an optimal number, location, and signal sound level of alarm devices. The alarm location problem was formulated as a nonlinear programming (NLP) problem and can be solved by appropriate optimization software tools. The method yields a minimum number of identical alarm devices, their locations at the ceiling of the facility, and the recommended signal sound level of the alarm device. Nevertheless, this method has three limitations: (1) an alarm device that can produce the signal sound level according to the recommendation might not be commercially available, (2) workers can only be present at the same locations as the machines, and (3) large alarm location problems might not be solvable since the alarm location problem is a combinatorial optimization problem.

However, the audibility of alarm systems is not the only factor that determines the effectiveness of auditory warnings. There are other cognitive and behavioral issues that also need to be considered. For further reading on auditory warnings, see Lazarus and Hoge (1986), Hellier, Edworthy and Dennis (1993), Edworthy (1994), Edworthy and Hellier (2000), Guillame *et al*. (2003), and Arrabito *et al*. (2004).

Additionally, a computer program called "Detectsound" that takes into account the effect of age on auditory sensitivity and frequency selectivity was developed by Laroche *et al.* (1991). Their program is a tool for assessing the audibility of warning signals and for designing safe sound signals. However, the program was designed only for existing alarm systems where all alarm devices were already installed. It does not recommend the optimal number and location of alarm devices.