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Improved particle swarm optimization to minimize periodic preventive maintenance cost for series-parallel systems

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ABSTRACT

This study minimizes the periodic preventive maintenance cost for a series-parallel system using an improved particle swam optimization (IPSO). The optimal maintenance periods for all components in the system are determined efficiently. Though having advantages such as simple understanding and easy operation, a typical particle swam optimization (PSO) is easily trapped in local solutions when optimizing complex problems and yields inferior solutions. The proposed IPSO considers maintainable properties of a series-parallel system. The importance measure of components is utilized to evaluate the effects of components on system reliability when maintaining a component. Accordingly, the important components form superior initial particles. Furthermore, an adjustment mechanism is developed to deal with the problem in which particles move into an infeasible area. A replacement mechanism is implemented that replaces the first *n* particles ranked in descending order of total maintenance cost with randomly generated particles in the feasible area. The purpose of doing so is overcome the weakness in that a typical PSO is easily trapped in local solutions when optimizing a complex problem. An elitist strategy is also applied within the IPSO. Additionally, this study employs response surface methodology (RSM) via systematic parameters experiments to determine the optimal settings of IPSO parameters. Finally, a case demonstrates the effectiveness of the proposed IPSO in optimizing the periodic preventive maintenance model for series-parallel systems.

1. Introduction

All equipment ages and deteriorates with usage and age. Preventive maintenance (PM) must be performed on a repairable series-parallel system to reduce failure rates and improve reliability. Notably, PM consumes human resources and time and has associated costs. However, nonessential services or an inadequate maintenance schedule wastes limited maintenance resources. The structure of a repairable series-parallel system markedly impacts system reliability. Establishing an appropriate maintenance strategy for a complex repairable system requires that maintenance priority of subsystems or components and their maintenance periods given limited maintenance resources be determined simultaneously. Maintenance quality is typically categorized into five classes – perfect maintenance, minimal maintenance, imperfect maintenance, worse maintenance and worst maintenance – according to degree of equipment restoration (Pham & Wang, 1996). Furthermore, to meet practical requirements, numerous studies have constructed maintenance models and optimization algorithms (Leou, 2006). However, the complexity of optimizing a maintenance model in a series-parallel system increases significantly as the number of components in a system increases. In such situations, obtaining the exact global optimum using analytical approaches via mathematical inference is impractical. Therefore, meta-heuristic algorithms, such as a genetic algorithm (GA) (Bris, Chatelet, & Yalaoui, 2003; Marseguerra & Zio, 2000), ant colony optimization (Samrout, Yalaoui, Chatelet, & Chebbo, 2005) and simulated annealing (Leou, 2006), are commonly employed to optimize these models and approach the global optimum.

Meta-heuristic algorithms commonly have three impediments to efficiently solving complex optimization problems (Battiti & Tecchiolli, 1994) – becoming trapped in local optimum, a limited cycle, and an inability to escape from a specific search region. These hindrances must be overcome when solving complex problems. Furthermore, when solving a constrained optimization problem using the particle swam optimization (PSO), an adjustment mechanism that moves particles back to a feasible area from an infeasible area is beneficial to optimized solutions (El-Gallad, El-Hawary, & Sallam, 2001; Hu & Eberhart, 2002; Parsopoulos & Vrahatis, 2002). Past studies (Baker & Ayechew, 2003) demonstrated that a superior initial population structure can significantly benefit the ability of meta-heuristic algorithm to approach the global optimum. Hence,

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numerous studies (Chen, Pan, Chao, & Lin, 2008; Shieh & May, 2001) have attempted to establish a superior initial population to enhance solving ability of current algorithms, particularly for solving complex problems. However, the idea regarding the establishment of the superior initial population in optimizing the preventive maintenance model for series-parallel systems has seldom been seen.

Kennedy and Eberhart (1995) developed the PSO in 1995. The PSO retains the advantages of easy understanding, simple operation, and rapid searching. However, when solving a large complex problem, PSO easily becomes trapped in local optimum. This weakness must be overcome to extend its practicability. Therefore, this study proposes an improved particle swarm optimization (IPSO) to overcome this weakness and thereby optimize the periodic preventive maintenance model for the series-parallel system. The maintenance period for each component in a system can thus be obtained. The properties of a preventive maintenance model for series-parallel systems, a constrained optimization model, are considered to create the improved mechanisms. Since the failure of any component can adversely affect the reliability of a series-parallel system, this study revises Birnbaum's importance measures of components (Elsayed, 1996) to appropriately adopt in assessing components importance form the aspect of preventive maintenance. This is because the calculation of Birnbaum's importance measures is based on a specific time. The values of importance measures vary with time given. The revised importance measures of components account for the adverse effect of components on system reliability given a component is failed during the time period from the start of system operating until the time system reliability reaching the allowable worst value. Additionally, the search mechanisms within the IPSO overcoming typical PSO weaknesses include: (1) An adjustment mechanism moves particles back into an feasible area from infeasible area by shortening maintenance periods for components scheduled to be maintained at the point of lowest reliability. (2) Replacement mechanism can enhance the search ability of particles in terms of exploration. The first *n* particles, which are ranked in a descending order for total maintenance cost, are replaced with randomly generated particles in the feasible area. (3) The elitist conservative strategy is employed, such that the best particle that with the lowest total maintenance cost through previous iterations is conserved to guide the other particles toward the superior positions. Additionally, this study employs response surface methodology (RSM) (Montgomery, 2005), a systematic parameter experiments from design of experiments to determine the optimal parameter settings for IPSO. Because the proposed IPSO is designed specifically for a preventive maintenance model for a series-parallel system, a related case from Bris et al. (2003) is used to demonstrate the effectiveness of the proposed improved search mechanisms for overcoming the typical PSO weakness. The proposed IPSO also compared with two approaches, one based on a genetic algorithm (Bris et al., 2003) and the other on ant colony optimization (Samrout et al., 2005), for the same case. Comparison results demonstrate the IPSO outperforms these two approaches.

2. Literature

2.1. Maintenance strategy of a series-parallel system

Maintenance is defined as activities that retain or restore the operational status of a system. Normally, maintenance can be classified as e-maintenance (Muller, Marquez, & Iung, 2008), corrective maintenance and preventive maintenance (Lie & Chun, 1986). E-maintenance is a new concept of maintenance. It contains predictive prognostics and condition-based monitor, and integrates existing telemaintenance principles with Web services and modern e-collaboration principles. Corrective maintenance includes minimal repairs and corrective replacement when a system fails. Preventive maintenance includes simple preventive maintenance and preventive replacement when a system is operating. The maintenance policies of a repairable deteriorating system are: (1) age-dependent PM policy, (2) periodic PM policy, (3) failure limit policy, (4) sequential PM policy, (5) repair limit policy, and (6) repair number counting and reference time policy (Wang, 2002). Periodic PM is widely used in practice simply because of its ease of implementation and management. This maintenance policy, applied in a series-parallel system with multiple components, received much attention. For example, Tsai, Wang, and Teng (2001) developed a periodic PM schedule for a system with deteriorating electro-mechanical components and optimized it using a GA. Leou (2006) proposed a novel algorithm for determining a maintenance schedule for a power plant. This algorithm combines the GA with simulated annealing to optimize maintenance periods and minimize maintenance and operational cost. Tsai, Wang, and Tsai (2004) also proposed a preventive maintenance policy for a multi-component system. Maintenance activities for components in each stage of PM were determined by maximizing the availability of the system for maintenance. Busacca, Marseguerra, and Zio (2001) focused on a high-pressure injection system at a nuclear power plant to establish a multi-objective optimization model to obtain a maintenance strategy using GA. Bris et al. (2003) proposed a periodic PM model that minimizes maintenance costs under the reliability constraint. The optimal maintenance period of each components after the first maintenance task for that component was determined using a GA. Samrout et al. (2005) optimized the Bris's case (2003) using the same procedure, but the ant colony optimization was adopted to optimize the maintenance periods for all components.

2.2. PSO introduction and application

The main idea behind PSO (Kennedy & Eberhart, 1995) is derived from the social behavior of populations with collaborative properties. For instance, birds flocking and fish schooling can move in the same direction via communication among individuals. The PSO imitates this species collaboration and is widely used in solving mathematical optimization problems. Each individual in a species population is a particle moving within a multidimensional search space and striving for the optimal solution. Thus, each particle corresponds to a candidate solution. Particles can adjust their positions toward their best positions according their experience and that of their neighboring particles. By continually adjusting their direction, all particles are expected to gradually approach the global optimum. The PSO has the advantages of easy understanding, simple operation, and rapid searching. A typical PSO generates an initial population randomly. Two factors including position and velocity characterize a particle status in a search space, as follows:

$$\mathbf{V}_i^{\text{new}} = \omega * \mathbf{V}_i + c_1 * \text{rand}_1 * (\mathbf{P}_i - \mathbf{X}_i) + c_2 * \text{rand}_2 * \left(\mathbf{P}_g - \mathbf{X}_i\right), \quad (1)$$

$$\mathbf{X}_i^{\text{new}} = \mathbf{X}_i + \mathbf{V}_i^{\text{new}}, \quad (2)$$

where $\mathbf{V}_i^{\text{new}}$ and $\mathbf{V}_i$ represent the updated velocity vector and current velocity vector in a search space for the *i*th particle, $\mathbf{X}_i$ represents the current position vector in a search space, $\mathbf{P}_i$ and $\mathbf{P}_g$ are currently the particle best solution and global solution. $\mathbf{P}_i - \mathbf{X}_i$ reveals the distance between $\mathbf{P}_i$ and $\mathbf{X}_i$, and $\mathbf{P}_g - \mathbf{X}_i$ is the distance between $\mathbf{P}_g$ and $\mathbf{X}_i$. rand_1 and rand_2 are two random functions with a range [0, 1]. c_1 and c_2 are positive constant parameters called acceleration coefficients controlling the movement steps of particles. $\mathbf{X}_i^{\text{new}}$ and $\mathbf{X}_i$ represent the updated position and current position of the *i*th particle. The ω is an inertia weight that controls, with