Cost Minimization for Joint Energy Management and Production Scheduling Using Particle Swarm Optimization

BY

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THESIS

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# NOMENCLATURE

## Uppercase

- **$BU_{it}$**: Contents in buffer $i$ at the beginning of interval $t$
- **$C_{part}$**: Cost per part ($/part$)
- **$CEM$**: Cost of extra maintenance resource ($$)
- **$CI$**: Holding cost ($$
- **$CR$**: Retrieved product cost ($$
- **$CU_{it}^{IS}$**: Cumulative inventory in holding space from buffer $i$ during interval $t$
- **$C^{Inventory}$**: Cost for storing one inventory unit ($/part$)
- **$C^{Retrieval}$**: Cost of retrieving one unit from an external source ($/part$)
- **$C^{ExtraCrew}$**: Cost of contracting one additional maintenance resource above $MC_r$ ($$/interval$$)
- **$EC$**: Electricity cost ($$$)
- **$H$**: Duration of the interval (minutes)
- **$INV_{it}$**: Amount of excess inventory incurred at buffer $i$ during interval $t$
- **$J$**: Number of time intervals in the planning horizon
- **$L(s)$**: Matrix for the location of each particle at iteration $s$ in PSO
- **$L_{gb}(s)$**: Global best solution for the swarm identified up to $s^{th}$ iteration in PSO
- **$L_{pg}(s)$**: Particle’s best solution recognized up to the $s^{th}$ iteration in PSO
- **$M$**: Number of stations in the manufacturing system
- **$MC$**: Maintenance cost ($$$)
- **$MC_r$**: Number of maintenance resources
- **$MEC$**: Maintenance electricity consumption cost ($$$)
- **$MP_i$**: Power consumption due to the maintenance task for station $i$ (kW)
- **$P^*$**: Total number of particles in the swarm, i.e., total population, in PSO
- **$P^*-p$**: Number of particles following avoidance PSO, i.e., population 2, in PSO
- **$PA$**: Committed power limitation (kW)
\( PDC \) Power demand cost considering both production and maintenance activities ($)

\( PEC \) Production electricity consumption cost ($)

\( PR_i \) Production rate of station \( i \) (parts/interval)

\( RP_i \) Rated power of station \( i \) (kW)

\( R_{i}^{Maintenance} \) Maintenance cost per interval of station \( i \) ($/interval)

\( R_{i}^{Electricity} \) Electricity consumption charge rate for interval \( t \) ($/kWh)

\( R^{power} \) Power demand charge rate throughout the planning horizon ($/kW)

\( RET_{u}^{bsBS} \) Number of units retrieved from external provider for buffer \( i \) in interval \( t \)

\( RET_{u}^{IS} \) Number of units retrieved from the holding space for buffer \( i \) in interval \( t \)

\( S_i \) Maximum capacity of buffer \( i \)

\( TA \) Target production throughput

\( TP \) Production throughput at the end of the production horizon

\( TPC \) Benefit/cost of surpassing/falling short of the production target ($)

\( V(s) \) Matrix of the velocity of individual particle at iteration \( s \) in PSO

\textbf{Lowercase}

\( br \) Bonus rate of additional production throughput in ($/part)

\( c_1 \) and \( c_2 \) Learning factors in PSO

\( l(s) \) Avoidance coefficient during iteration \( s \) in PSO

\( p \) Number of particles following standard PSO, i.e., population 1, in PSO

\( pr \) Penalty rate of the production loss in ($/part)

\( ri_{it} \) Production efficiency of station \( i \) during interval \( t \)

\( si_{it} \) Percentage of time station \( i \) is up during interval \( t \) considering station setup time

\( w_1 \) and \( w_2 \) Random real numbers between 0 and 1 in PSO

\( w_i \) Setup time of station \( i \) after maintenance
**Greek Letters**

- $\alpha(s)$: Inertial weight during iteration $s$ in PSO
- $\alpha_{max}$: Maximum inertial weight value in PSO
- $\alpha_{\text{min}}$: Minimum inertial weight value in PSO
- $\gamma(s)$: Avoidance rate during iteration $s$ in PSO

**Decision Variables**

- $e_{it}$: Binary decision variable to denote the ON/OFF decision for station $i$ in interval $t$.
- $m_{it}$: Binary decision variable for maintenance actions for station $i$ in interval $t$.

**Indices**

- $i$: Index of stations
- $j_{it}$: Index of the degradation states of station $i$
- $m$: Index representing the particles in population 1 in PSO, $m \in \{1, 2, \ldots, p\}$
- $n$: Index representing the particles in population 2 in PSO, $n \in \{p+1, \ldots, P^*\}$
- $o$: Index representing the particles in total population in PSO, $o \in \{1, 2, \ldots, P^*\}$
- $s$: Index of PSO iterations
- $s_{\text{max}}$: Index of the final iteration in PSO
- $t$: Index of time intervals

**Sets**

- OP: Set of intervals that belong to on peak period
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
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<tr>
<td>ANOVA</td>
<td>Analysis of Variance</td>
</tr>
<tr>
<td>DOE</td>
<td>Design of Experiments</td>
</tr>
<tr>
<td>EIA</td>
<td>Energy Information Administration</td>
</tr>
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<td>EPA</td>
<td>Environmental Protection Agency</td>
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SUMMARY

Production costs account for the largest share of the overall cost of manufacturing facilities. With the U.S. industrial sector becoming more and more competitive, manufacturers are looking for more cost and resource efficient working practices. Operations management and production planning have shown their capability to dramatically reduce manufacturing costs and increase system robustness. When implementing operations related decision making and planning, two fields that have shown to be most effective are maintenance and energy. Unfortunately, the current research that integrates both is limited. Additionally, these studies fail to consider parameter domains and optimization on joint energy and maintenance driven production planning.

Accordingly, production planning methodology that considers maintenance and energy is investigated. Two models are presented to achieve well-rounded operating strategy. The first is a joint energy and maintenance production scheduling model. The second is a cost per part model considering maintenance, energy, and production. The proposed methodology will involve a Time-of-Use electricity demand response program, buffer and holding capacity, station reliability, production rate, station rated power, and more. In practice, the scheduling problem can be used to determine a joint energy, maintenance, and production schedule. Meanwhile, the cost per part model can be used to: (1) test the sensitivity of the obtained optimal production schedule and its corresponding savings by varying key production system parameters; and (2) to determine optimal system parameter combinations when using the joint energy, maintenance, and production planning model.

Additionally, a factor analysis on the system parameters is conducted and the corresponding performance of the production schedule under variable parameter conditions, is
evaluated. Also, parameter optimization guidelines that incorporate maintenance and energy parameter decision making in the production planning framework are discussed. A modified Particle Swarm Optimization solution technique is adopted to solve the proposed scheduling problem. The algorithm is described in detail and compared to Genetic Algorithm. Case studies are presented to illustrate the benefits of using the proposed model and the effectiveness of the Particle Swarm Optimization approach.

Numerical Experiments are implemented and analyzed to test the effectiveness of the proposed model. The proposed scheduling strategy can achieve savings of around 19 to 27 % in cost per part when compared to the baseline scheduling scenarios. By optimizing key production system parameters from the cost per part model, the baseline scenarios can obtain around 20 to 35 % in savings for the cost per part. These savings further increase by 42 to 55 % when system parameter optimization is integrated with the proposed scheduling problem. Using this method, the most influential parameters on the cost per part are the rated power from production, the production rate, and the initial machine reliabilities.

The modified Particle Swarm Optimization algorithm adopted allows greater diversity and exploration compared to Genetic Algorithm for the proposed joint model which results in it being more computationally efficient in determining the optimal scheduling. While Genetic Algorithm could achieve a solution quality of $2,279.63 at an expense of 2,300 seconds in computational effort. In comparison, the proposed Particle Swarm Optimization algorithm achieved a solution quality of $2,167.26 in less than half the computation effort which is required by Genetic Algorithm.
1 INTRODUCTION

According to the U.S. Energy Information Administration (EIA), the manufacturing sector accounts for 31% of the total energy consumption, making it the largest consumer of energy in the United States as shown in Figure 1.1 (U.S. Energy Information Administration, 2011). The industrial sector alone consumes 52% of the energy consumed worldwide (U.S. Energy Information Administration, 2013). Over the past twenty years, due to infrastructure upgrades, increase in fossil fuel prices, and stricter climate change legislation, energy prices are rising (Bloomenergy, 2008). The manufacturing sector consumes a large amount of electrical energy for process heating, machine driving, ventilation and air conditioning, and other areas (Energy Information Administration, 2011).

![Figure 1.1 End use sector share of Total consumption (2011)](source: Energy Information Administration. Annual Energy Review 2011)
Growing demand for electricity has given rise to more electricity generation and distribution equipment since it is a form of energy that needs to be generated, distributed and consumed immediately. It is estimated that an investment of approximately $1.5 trillion to $2 trillion will be required to meet the growing energy demand by the year 2030 (Chupka et al., 2008). Another potential concern with the growing energy demand is Greenhouse Gases (GHG). The major source of GHG emissions in the United States is from electricity generation. Global warming and climate change are a result of the rise in GHG emissions and are a threat to the sustainability of the ecosystem (U.S. EPA, 2015).

![Figure 1.2 Total U.S. Greenhouse Gas Emissions by Economic Sector in 2015](Source: U.S. EPA, 2015)

Energy considerations have begun to gain popularity in more recent years because of rising concerns on GHG emissions. Specifically, energy efficiency and demand response considerations in production planning have gained much attention due to high energy costs and environmental concerns of the society.
To curb the potential negative impacts on the environment, two important points that the manufacturing production planner needs to focus on to achieve a robust operation and low production costs, are maintenance and energy. Maintenance has a high influence on the overall stability of the production system and hence is regarded as a precedence in production planning. Maintenance consumes a lot of resources and time, but scheduled maintenance is known to increase system stability. Incorporating maintenance in production planning has been reported by several research studies (Jin et al., 2009; Nourelfath et al., 2016; Xiao et al., 2016; Xia et al., 2015; Beheshti-Fakher et al., 2016; Fitouhi et al., 2014; and Li et al., 2009). Consequently, several studies have been conducted investigating the incorporation of integrating energy consumption, costs, and availability into production planning decision making (Sun and Li, 2013; Feng et al., 2016; Li and Sun, 2013; Gajic et al., 2016; Beier et al., 2017; Wang and Li, 2013; Wang and Li, 2014; and Gong et al., 2015).

Including energy and maintenance considerations in production planning by further advancing production planning frameworks may lead to several additional opportunities in cost reduction and environmental sustainability. There are several research studies that investigate the integration of either energy or maintenance in production planning, however there is a lack of literature for research which integrates both simultaneously. Energy and maintenance have been simultaneously considered in two research studies conducted (Yao et al., 2016; and Yao et al., 2015). These studies evaluate the feasibility of joint energy and maintenance decision making by developing simulation models. Time variable energy costs are used to reschedule the maintenance activities. Comparison is done for the maintenance cost, energy consumption cost, and throughput due to different rescheduling policies. These studies proved that rescheduling strategies can lead to benefits from both energy cost reduction and productivity improvement.
However, these studies required several assumptions and the use of simulation models needing long build times. Thus, there is a definite need to develop production planning and decision making tools that consider both energy and maintenance related variables, to achieve the potential benefits.

The challenges that arise when integrating maintenance, energy, and production decision making are from the availability of parameter data and complexity, and from the solvability of the problem. In this study, a production planning methodology has been presented that considers maintenance and energy simultaneously. The study presents two models. The first model considers joint energy and maintenance production scheduling. The second model is a cost per part model considering maintenance and energy costs. However, balancing the different features of the problem to achieve a robust and economic operating plan is difficult due to nonlinear effects of system parameters and governing functions.

To address the issue of available parameter data and complexity, sensitivity analysis and Design of Experiments (DOE) (Montgomery, 1991) are used to study the behavior of the proposed system under different production schedules and parameter settings. These methods can help determine the behavior of both the physical system and the effectiveness of the proposed model when sufficient data is not available (Kleijnen, 1999). Hence, a DOE based $3^k$ factorial design procedure is constructed and the interactions among the different factors are evaluated.

Moreover, to address the issues related to the solvability of the problem, it is important to identify an appropriate optimization solution algorithm. Optimization algorithms can be roughly separated into two categories: exact algorithms and heuristics. Given sufficient time and space, exact methods (e.g. enumerative, linear and integer programming, branch and bound, dynamic
programming, etc.) can guarantee that an optimal solution is obtained in a finite time. However, they are often extremely time consuming for very difficult optimization problems such as global optimization or NP-hard problems (Woeginger, 2003; Hertz and Widmer, 2003).

Due to the large dimensionality of the problem and nonlinear characteristics of the formulation, optimal scheduling is challenging and is recognized to be a NP-Hard problem (Yuan and Ghanem, 2016; and Hemmecke et al., 2010). Even for the simplest production lines that are considered (i.e. for example a single product serial line), scheduling is challenging due to nonlinear buffer and production constraints, nonlinear objective function costs, and discontinuous energy costs.

For such problems, the finite time solving capability of exact methods may increase exponentially with respect to the dimensions of the problem. While the second category of optimization algorithms, heuristics, proves to be more flexible and powerful search technique. Heuristics only obtain suboptimal solutions and cannot converge to the global optimal solution; nevertheless, they provide acceptable solutions that are sufficient for practical purposes in a limited time.

Many heuristic algorithms focus more on the particularities of the problem making it more problem dependent. On the other hand, a metaheuristic (robust heuristic) is a high-level problem independent algorithmic framework. This enables researchers to develop heuristic and/or metaheuristic optimization algorithms (Hertz and Widmer, 2003; Luke, 2010).

A local search metaheuristic algorithm can be successfully adapted to a combinatorial optimization problem by fine tuning its intrinsic parameters, appropriately modeling the initial solution for local search, and defining a search space with neighborhood solutions where the
search can proceed to find better solutions. Defining the search space by relaxing some of the problem constraints and adding a penalty term for its violation in the cost function can help the algorithm explore the solution space more thoroughly and arrive at the feasible solutions much faster.

Thus, a need to use heuristic and/or metaheuristic methods for solving such production scheduling problems is recognized in the literature. One such local search metaheuristic algorithm used in this thesis to generate optimal schedules for the proposed joint energy and maintenance production planning problem, is Particle Swarm Optimization (PSO). Additionally, the PSO is modified to incorporate strategies (i.e. local optimal avoidable strategy and time varying inertia weight) to improve the computational capability of the PSO to arrive at an optimal schedule as found in literature.

This thesis can help manufacturing management in joint energy, maintenance, and production scheduling; and identification of important system parameters. Also, this work can help determine the rationality of using such joint methods for different domains of system parameters or cost values. Finally, the rest of the thesis is organized as follows. In Section 2, a joint energy and maintenance production scheduling problem and a cost per part model considering maintenance and energy are presented. Next, in Section 3, a sensitivity analysis is conducted and DOE methodology is used to study the behavior of the system under different production schedules and parameter settings. In Section 4, the modified PSO is introduced and extensive numerical results are presented. Finally, Section 5 will go over the conclusions and future work.
2 METHODOLOGY AND MODEL BUILDING

2.1 Methodology

In this section, two different models for employing joint energy and maintenance production planning are presented. In the first model, i.e. production scheduling model, a TOU electricity demand response program and the station degradation over time are considered. In the second model, i.e., cost per part model, the cost of each part is derived from the proposed joint energy and maintenance scheduling problem.

The electricity demand response program, used in the first problem, can be defined as the alteration in electricity usage by the end use customers in response to the variations in time based electricity price or incentive payments to encourage lower electricity use at times of high electricity demand (Federal Energy Regulatory Commission, 2013). The decision variables considered in the production line are the schedule for “on/off” station states and the maintenance schedule for all the stations throughout the production horizon. These schedules are obtained such that electricity costs and maintenance costs are minimized throughout the production horizon, and production throughput is maximized.

The second model is on the cost per part derived from the proposed scheduling problem. The variables of interest for this model are the system parameters, and it is assumed that the production schedule is previously identified. The parameters considered are the rated power of the stations, maintenance power demand, production rate of the stations, initial station reliability, buffer initial contents, and number of maintenance resources. Furthermore, holding and maintenance resource cost functions are integrated into the cost per part model.

It is important to determine energy and maintenance schedules jointly while understanding and manipulating system parameters. Thus, the two models complement each
other when applying joint energy and maintenance production planning to achieve more accurate and robust operations.

The system considered in the models is a serial production line with $M$ stations and $M-1$ buffers, which is shown in Figure 2.1.

![Figure 2.1 Serial $M$ Station $M-1$ Buffer Production System](image-url)
### 2.1.1 Production Scheduling Problem

In this model, the planning horizon is divided into \( T \) fixed intervals, and the duration of every interval in this production horizon is \( H \). The notation \( e_{it} \) is used to represent the energy driven station schedule and \( m_{it} \) is used to represent the station maintenance schedule for station \( i \) during time interval \( t \). Also, a TOU electricity demand response program is considered for the scheduling problem throughout the production horizon. The goal is to minimize the electricity billing cost, maintenance cost, and throughput cost as shown in (1). Meanwhile, the constraints are shown in (2)-(5) as follows.

\[
\begin{align*}
\min_{e_{it}, m_{it}} (MC + EC + TPC) \\
\max_{i \in OP} \left( \sum_{t=1}^{M} e_{it} \cdot RP_i \cdot s_{it} + \sum_{t=1}^{M} m_{it} \cdot MP_i \right) & \leq PA \\
\sum_{i=1}^{M} m_{it} & \leq MCr, \ \forall t \\
0 & \leq BU_{it} \leq S_i, \ i = 1, \ldots, M - 1, \ \forall t \\
m_{it} e_{it} & = 0, \forall i, \forall t
\end{align*}
\]

In (1), \( MC \), \( EC \), and \( TPC \) are the maintenance cost, electricity billing cost, and throughput cost, respectively. Their formulations are shown in (6)-(8).

\[
MC = \sum_{j=1}^{J} \sum_{i=1}^{M} (1 - e_{it}) \cdot m_{it} \cdot R_i^{Maintenance}
\]

\[
EC = PEC + MEC + PDC
\]

\[
TPC = pr \cdot \max(TA - TP, 0) - br \cdot \max(TP - TA, 0)
\]
Where $R_{i}^{Maintenance}$ is the unit cost of maintenance for station $i$; $PEC$ is the cost of electricity consumption for production; $MEC$ is the cost of electricity consumption for maintenance; $PDC$ is the power demand cost; $TA$ is the production target for the production horizon; $TP$ is the production throughput; $pr$ is the rate of penalty per production unit lost (i.e. $TP < TA$); $br$ is the bonus rate per extra unit produced above the specified level $TA$ (i.e. $TP > TA$).

The formulations of $PEC$, $MEC$, and $PDC$ are shown in (9)-(11).

$$PEC = \sum_{i=1}^{J} H \cdot R_{i}^{Electricity} \cdot \left[ \sum_{t=1}^{M} e_{it} \cdot RP_{i} \cdot s_{it} \right]$$

(9)

$$MEC = \sum_{i=1}^{J} H \cdot R_{i}^{Electricity} \cdot \left[ \sum_{t=1}^{M} m_{it} \cdot MP_{i} \right]$$

(10)

$$PDC = R^{power} \cdot \max_{t \in OP} \left( \sum_{t=1}^{M} e_{it} \cdot RP_{i} \cdot s_{it} + \sum_{t=1}^{M} m_{it} \cdot MP_{i} \right)$$

(11)

Where $R_{i}^{Electricity}$ is the electricity consumption rate ($$/kWh) for interval $t$; $R^{power}$ is the power demand rate ($$/kW) throughout the planning horizon; $OP$ is the set of intervals during on peak period; $RP_{i}$ is the power rating of station $i$; $s_{it}$ is the percentage of time station $i$ is active during interval $t$ considering station setup time; and $MP_{i}$ is the required power consumption due to the maintenance task for station $i$. The station uptime, $s_{it}$, can be formulated by (12), where $w_{i}$ is the setup time of station $i$.

$$s_{it} = \begin{cases} 1, & \text{if } m_{i(t-1)} = 0 \text{ and } m_{it} = 0 \\ 1 - \left( \frac{w_{i}}{H} \right), & \text{if } m_{i(t-1)} = 1 \text{ and } m_{it} = 0 \end{cases}$$

(12)
Let $PR_M$ denote the production rate of station $M$, and $r_{Mt}$ denote the reliability of the station $M$ during interval $t$. The production throughput can be formulated as shown in (13).

$$TP = \sum_{i=1}^{j} (1 - m_{Mt}) \cdot e_{Mt} \cdot s_{Mt} \cdot PR_M \cdot r_{Mt} \cdot H$$

(13)

Lastly, $BU_i$, the buffer contents for buffer $i$ at the start of interval $t$, can be formulated as shown in (14).

$$BU_i = BU_{i(i-1)} + e_{i(i-1)} \cdot s_{i(i-1)} \cdot PR_{i} \cdot r_{i(i-1)} \cdot H - e_{i(i+1)(i-1)} \cdot s_{i(i+1)(i-1)} \cdot PR_{i+1} \cdot r_{i(i+1)(i-1)} \cdot H$$

(14)

The maintenance task is triggered based on the station reliability, $r_{it}$, which degrades over time. The maintenance task cannot be performed when the station is scheduled to be “on” for production as expressed in equation (5).
2.1.2 Production Scheduling Problem Solution Approach

A challenge is faced when seeking to implement the proposed problem and determining an optimal production schedule that minimizes the costs. In general, scheduling problems are nonlinear binary programming problems which are found to be NP-Hard (Yuan and Ghanem, 2016; and Hemmecke et al., 2010). Thus, it is evident that heuristic and/or metaheuristic methods are applied for solving such problems. Consequently, Particle Swarm Optimization (PSO) is used to solve the scheduling problem. The solvability of the problem will be discussed with more details in Section 4.

PSO is a population based stochastic, iterative evolutionary approach which stresses collaboration in the search procedure by considering particle location and velocity (Clerc, 2010). PSO is utilized to achieve a near optimal energy and maintenance schedule for the model described in Section 2.1.1. The PSO algorithm will be evaluated and its effectiveness will be analyzed by comparing with the Genetic Algorithm (GA) approach (which will also be discussed in greater details in Section 4).

For the proposed joint energy and maintenance production planning problem, the fitness function used to execute the PSO is formulated as shown in (15). Representation of constraints of scheduling problems in the application of metaheuristics is important. To guide the search into the feasible subregion(s), constraints are mapped into the objective function using penalty functions (Harjunkoski et al., 2014). Constraints (2)-(5) are integrated as penalty terms in the fitness function for the proposed problem in Section 2.1.
\[ MC + EC + TPC + A_1 \cdot \left[ \min(PA - \max_{i \in OP} \left( \sum_{i=1}^{M} e_i \cdot RP_i \cdot s_{ii} + \sum_{i=1}^{M} m_{ii} \cdot MP_i \right), 0) \right]^2 \]
\[ + A_2 \cdot \sum_{i=1}^{M} \left[ \min(MCr - \sum_{i=1}^{M} m_{ii}, 0) \right]^2 + A_3 \cdot \sum_{i=1}^{M-1} \sum_{i=1}^{f} \left[ \min(S_i - BU_{ii}, 0) \right]^2 \]
\[ + A_4 \cdot \sum_{i=1}^{M-1} \sum_{i=1}^{f} \left[ \min(BU_{ii}, 0) \right]^2 + A_5 \cdot \sum_{i=1}^{M} e_{ii} \cdot m_{ii} \]

The violation of constraints (2)-(5) are magnified by corresponding real numbers \( A_1, A_2, A_3, A_4, \) and \( A_5 \) which represents the incurred penalties in the objective function.

Assuming the system parameters such as the station production rate, the power rating of the station, the station reliabilities, etc. are all available, the presented methodology and solution procedure can be utilized to recognize the near optimal production schedule.
2.2 Cost Per Part Model

A unit cost model for the cost per part which can be obtained from the scheduling problem is presented. This model contains maintenance cost, energy costs, throughput cost, and production throughput. Furthermore, holding cost and added maintenance resource cost formulations are incorporated into the cost per part model to account for any violations of constraints (3) or (4).

The cost per part model allows the manufacturers to evaluate all cost sources simultaneously and can be used in higher level managerial decision making and operations management. This measure can help provide understanding on production capability thresholds. The cost per part, $C_{\text{part}}$, is formulated as shown in (16).

$$C_{\text{part}} = \frac{MC + EC + TPC + (CI + CR + CEM)}{TP}$$  \hspace{1cm} (16)

$MC$, $EC$, and $TPC$ are obtained from (6)-(8). $CI$ is the cost of holding surplus parts that exceed maximum capacity of buffers. Also, to account for empty buffer situations, some parts are provided externally resulting in a retrieved product cost of $CR$. Lastly, $CEM$ represents for the cost when additional maintenance resources, above the level of $MCr$, are essential. $CI$ is formulated as shown by (17).

$$CI = \sum_{i=1}^{M-1} \sum_{t=1}^{I} INV_{it} \cdot C^{\text{Inventory}}$$  \hspace{1cm} (17)

$C^{\text{Inventory}}$ is the cost for holding one excess part and $INV_{it}$ is the quantity of excess parts produced corresponding to buffer $i$ during interval $t$. $INV_{it}$ is formulated as shown by (18).
\[
INV_i = \begin{cases} 
BU_i - S_i, & \text{if } BU_i > S_i \\
0, & \text{if } 0 \leq BU_i \leq S_i 
\end{cases} (18)
\]

Next, \( RET_{i}^{BS} \) signifies the number of units salvaged from an external provider when the contents of buffer \( i \) during interval \( t \) drop below the minimum buffer capacity (zero). It is also considered that the additional units are initially provided (at no cost) from the holding space produced prior to interval \( t \). Consequently, the cumulative inventory in the holding space, \( CU_{i}^{IS} \), corresponding to buffer \( i \) during interval \( t \) is formulated as shown in (19).

\[
CU_{i}^{IS} = CU_{i(t-1)}^{IS} + INV_i - RET_{i}^{IS} \quad (19)
\]

Where \( RET_{i}^{IS} \) is the number of units salvaged from the holding space. The additional units required are attained from an external provider in a situation when \( CU_{i}^{IS} = 0 \). The number of units retrieved from holding space, \( RET_{i}^{IS} \), and the number of units retrieved from an external provider when the inventory in the holding space has emptied, \( RET_{i}^{BS} \), are formulated as shown in (20) and (21), respectively.

\[
RET_{i}^{IS} = \begin{cases} 
-BU_i, & \text{if } BU_i < 0 \text{ and } CU_{i}^{IS} \geq -BU_i \\
CU_{i}^{IS}, & \text{if } BU_i < 0 \text{ and } 0 < CU_{i}^{IS} < -BU_i \\
0, & \text{if } (BU_i < 0 \text{ and } CU_{i}^{IS} = 0) \text{ or } 0 \leq BU_i \leq S_i 
\end{cases} \quad (20)
\]

\[
RET_{i}^{BS} = \begin{cases} 
-BU_i, & \text{if } BU_i < 0 \text{ and } CU_{i}^{IS} = 0 \\
-BU_i - CU_{i}^{IS}, & \text{if } BU_i < 0 \text{ and } 0 < CU_{i}^{IS} < -BU_i \\
0, & \text{if } (BU_i < 0 \text{ and } CU_{i}^{IS} \geq -BU_i) \text{ or } 0 \leq BU_i \leq S_i 
\end{cases} \quad (21)
\]

Eventually, the retrieved product cost, \( CR \), due to parts retrieved from an external provider to overcome buffer shortages can be formulated as shown in (22), where \( C^{\text{Retrieval}} \) is the cost of retrieving one unit from an external source.
\[
CR = \sum_{i=1}^{M-1} \sum_{t=1}^{T} RET_{it}^{inBS} C^{Retrieval}
\] (22)

Since, the buffer restrictions have been accounted for in the cost per part by considering holding and out of house retrieval costs, \( BU_{it} \) can assume negative values to represent buffer deficiencies. However, \( RET_{it}^{inS} = -BU_{it} \geq 0 \) and \( RET_{it}^{inBS} = -BU_{it} \geq 0 \) constraints are incorporated.

Finally, \( CEM \), the cost when additional maintenance resources are needed is shown in formulation (23). \( C^{ExtraCrew} \) is the unit cost of contracting an additional maintenance resource above the \( MCr \) level.

\[
CEM = \sum_{t=1}^{T} \max(0, \sum_{i=1}^{M} m_{it} - MCr) \cdot C^{ExtraCrew}
\] (23)

\( CI, CR, \) and \( CEM \) are essential to realize feasible production plans because the production schedule does not consider the uncertainty due to variation in system parameter values. Overall, the cost per part model is a valuable device for manufacturers. It can be used for determining optimal system parameter combinations when manufacturers are looking for making physical modifications to their production line and eventually help recognize which parameters are critical to reduce cost and error in the production system.
3 CASE STUDY AND ANALYSIS

A case study representing the joint energy and maintenance production planning problem from Section 2.1 is implemented. In this case study, first, the benefits of using the joint energy, maintenance, and production planning problem compared to the baseline cases are highlighted; subsequently, a one-factor-at-a-time analysis and a multifactor analysis are implemented. The production schedule and various system parameter settings are varied in the factor analysis to determine the sensitivity on the cost per part.

Design of Experiment (DOE) method and sensitivity analysis can help determine the performance of real life systems and the adequacy of the proposed scheduling model when data availability is not sufficient (Kleijnen, 1999). The evaluation of the one-factor-at-a-time analysis is done graphically. On the other hand, DOE method is used in the multilevel factor analysis which reflects a higher dimensionality owing to combinations of factors. Most critical parameters are determined by analyzing the interactions among the different factors using DOE based $3^k$ full factorial design (Montgomery, 1991).

A serial production line with five stations and four buffers setup as shown in Figure 3.1 is considered.

Figure 3.1 Serial Five Station Four Buffer Production System
3.1 Comparison to Baseline Case

The results for the proposed scheduling model are compared with the two baseline cases. The first baseline case lacks a dynamic energy control plan and all $e_{rt}$ states are set equal to 1 unless buffer constraints are violated. Meanwhile, the maintenance plan is triggered by a threshold reliability. The second baseline case controls energy and maintenance decisions separately. Here, $e_{rt}$ is attained by minimizing the electricity billing cost under the restriction of production target while the maintenance, $m_{rt}$, is determined considering a threshold reliability. The three scenarios are summarized in Table 3.1.

<table>
<thead>
<tr>
<th>Scenario I</th>
<th>No energy control, production efficiency triggered maintenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario II</td>
<td>Energy control and maintenance are implemented separately</td>
</tr>
<tr>
<td>Scenario III</td>
<td>Proposed joint energy, maintenance and production planning model</td>
</tr>
</tbody>
</table>

The initial system parameter values such as production rate, rated power, setup times, initial buffer contents etc. are summarized in Table 3.2 and Table 3.3. Meanwhile, the production and maintenance schedules for the proposed problem are obtained using the PSO method introduced in Section 2.1.2. The best PSO method, which will be further described in Section 4.2 using numerical results on solution quality and computation time, is used here to obtain the schedules for the proposed problem.

PSO is used with a swarm size of 3,000 to solve the proposed problem. The maximum iteration number, $s_{max}$, is set to 500. The learning factors $c_1$ and $c_2$ are set to 2. And $w_1$ and $w_2$
are real numbers chosen randomly between 0 and 1. The inertial weight parameters \( \alpha_{\text{max}} \) and \( \alpha_{\text{min}} \) are 0.9 and 0.4, respectively.

### Table 3.2 Basic Station Parameters

<table>
<thead>
<tr>
<th>( i )</th>
<th>Station Production Rate (parts/hr)</th>
<th>Station Rated Power (kW)</th>
<th>Setup Time (minutes)</th>
<th>Maintenance Cost Per Interval ($/hr)</th>
<th>Maintenance Power (kW)</th>
<th>Initial Station Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>15</td>
<td>3</td>
<td>60</td>
<td>1.5</td>
<td>90%</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>17</td>
<td>2</td>
<td>100</td>
<td>2</td>
<td>85%</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>24</td>
<td>2.5</td>
<td>80</td>
<td>2</td>
<td>90%</td>
</tr>
<tr>
<td>4</td>
<td>50</td>
<td>17</td>
<td>4</td>
<td>72</td>
<td>1.5</td>
<td>90%</td>
</tr>
<tr>
<td>5</td>
<td>50</td>
<td>21</td>
<td>2</td>
<td>88</td>
<td>2</td>
<td>90%</td>
</tr>
</tbody>
</table>

Incumbent Cost per part ($) 1.59

### Table 3.3 Basic Buffer Parameters

<table>
<thead>
<tr>
<th>Buffer</th>
<th>Initial Buffer Content</th>
<th>Maximum Buffer Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>70</td>
<td>160</td>
</tr>
<tr>
<td>2</td>
<td>70</td>
<td>145</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>140</td>
</tr>
<tr>
<td>4</td>
<td>75</td>
<td>160</td>
</tr>
</tbody>
</table>

The number of maintenance resources, \( MCr \), is 2. The threshold reliability for all stations is 0.7 for Scenarios I and II, and 0.75 for Scenario III. For Scenarios I and II, the maintenance is triggered when the threshold reliability is reached and continued until the reliability is restored to 0.9. The production target per week is 1,400 parts. Producing an additional unit above the target
throughput involves a bonus rate of $3 per part, while falling short of target throughput by a unit incurs a penalty rate of $5 per part. The planning horizon is for an 8-hour shift (between 7:00 AM-3:00 PM) over a 5-day week and it is divided into 160 15-minute intervals. The peak period is between 1:00 PM to 3:00 PM during all days of the week. Table 3.4 summarizes the time-of-use rates which consists of both consumption and demand charges.

### Table 3.4 TOU Program

<table>
<thead>
<tr>
<th>Time of Day</th>
<th>Consumption Rate ($/kWh)</th>
<th>Demand Rate ($/kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7:00AM-1:00PM</td>
<td>0.08274</td>
<td>0</td>
</tr>
<tr>
<td>1:00PM-3:00PM</td>
<td>0.16790</td>
<td>18.8</td>
</tr>
</tbody>
</table>

After solving the problem using PSO method described previously in Section 2.1.2, the schedules for production and maintenance for the proposed problem are obtained corresponding to the objective function in (15) and results attained are compared with Scenarios I and II.

Table 3.5 shows the throughput obtained for each scenario and it is apparent that the target throughput is achieved in all three scenarios.

### Table 3.5 Comparison of Throughput

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Throughput</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>1,526</td>
</tr>
<tr>
<td>II</td>
<td>1,418</td>
</tr>
<tr>
<td>III</td>
<td>1,419</td>
</tr>
</tbody>
</table>
Table 3.6 shows the electricity consumed (kWh) during production and from the maintenance activity conducted for each scenario. The power demand (kW) across the three scenarios is also compared in Table 3.6. The results show that Scenario I has much higher power demand compared to Scenarios II and III. Furthermore, the electricity consumed in Scenario III due to maintenance action is much lower when compared to Scenarios I and II. This is because the number of stations scheduled for maintenance across the production horizon is fewer in Scenario III. This suggests that by using the proposed scheduling model several unnecessary maintenance activities can be minimized and thus achieve more resourceful maintenance action plan.

**Table 3.6 Electricity Consumption and Power Demand**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Production Electricity Consumption (kWh)</th>
<th>Maintenance Electricity Consumption (kWh)</th>
<th>Total Electricity Consumption (kWh)</th>
<th>Power Demand (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>3,417.7</td>
<td>27.50</td>
<td>3,445.20</td>
<td>94</td>
</tr>
<tr>
<td>II</td>
<td>3,128.9</td>
<td>22.37</td>
<td>3,151.27</td>
<td>79</td>
</tr>
<tr>
<td>III</td>
<td>3,439.3</td>
<td>10.87</td>
<td>3,450.17</td>
<td>79</td>
</tr>
</tbody>
</table>

The total cost, energy related cost, and the non-energy related maintenance cost for Scenarios I-III are summarized in Table 3.7 and Figure 3.2. As anticipated, Scenario III achieves a much lower total cost compared to Scenarios I and II. This is due to very low non-energy related maintenance cost for Scenario III compared to that from Scenarios I and II. Thus, it suggests that the proposed scheduling model is both essential and productive.
Table 3.7 Comparison of Total Cost ($)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Energy Cost (Electricity+ Demand)</th>
<th>Non-Energy Cost (Maintenance)</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>2,124.78</td>
<td>1,240</td>
<td>3,364.78</td>
</tr>
<tr>
<td>II</td>
<td>1,801.70</td>
<td>1,018</td>
<td>2,819.70</td>
</tr>
<tr>
<td>III</td>
<td>1,832.37</td>
<td>493</td>
<td>2,268.36</td>
</tr>
</tbody>
</table>

Figure 3.2 Energy and Maintenance Cost Comparison

The final throughput produced may be different in the three scenarios presented. So, to better assess the three scenarios, a comparison using the cost per part metric is performed and the results are presented in Table 3.8. It is observed that the proposed scheduling model in Scenario III attains the least unit cost among all the three scenarios. Furthermore, Table 3.9 illustrates the
percentage decrease in cost per part produced when using the proposed model in Scenario III compared to the baseline models used in Scenarios I and II.

Table 3.8 Cost Per Part Produced

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Cost per part ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>2.205</td>
</tr>
<tr>
<td>II</td>
<td>1.989</td>
</tr>
<tr>
<td>III</td>
<td>1.599</td>
</tr>
</tbody>
</table>

Table 3.9 Reduction of Cost Per Part Produced when using Proposed Model

<table>
<thead>
<tr>
<th>Comparison between scenarios</th>
<th>Cost reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>III vs I</td>
<td>27.48%</td>
</tr>
<tr>
<td>III vs II</td>
<td>19.61%</td>
</tr>
</tbody>
</table>

As seen from the results, the proposed model in Scenario III produces significantly better cost efficiency when compared to the schedules obtained from the baseline models in Scenarios I and II wherein the implementation of energy and maintenance control is done disjointedly.
### 3.2 Single Factor Analysis

Profitability can be significantly affected by the parameters of the cost per part. Hence, several key parameters are studied in the sensitivity analysis. The station’s rated power, the maintenance’s rated power, and the initial buffer levels are determined based on percent of the nominal values from Tables 3.2 and 3.3. The station production rate, initial station reliability; and the number of maintenance resources is varied based on their original unitary values. Table 3.10 summarizes the factor values analyzed.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>$RP_i$</td>
<td>80%, 85%, 90%, 95%, 105%, 110%</td>
</tr>
<tr>
<td>$MP_i$</td>
<td>80%, 90%, 110%, 120%, 130%, 140%, 150%</td>
</tr>
<tr>
<td>$PR_i$</td>
<td>40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90</td>
</tr>
<tr>
<td>$r_i(t=1)$</td>
<td>0.65, 0.7, 0.75, 0.8, 0.85, 0.9</td>
</tr>
<tr>
<td>$BU_i(t=1)$</td>
<td>0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 100%</td>
</tr>
<tr>
<td>$MCr$</td>
<td>1,2,3,4,5</td>
</tr>
</tbody>
</table>

The graphical results based on the system parameter values shown in Table 3.10 are presented in Figure 3.3.
Figure 3.3 Change in Cost Per Part For: (a) Percent of Station Rated Power; (b) Percent of Maintenance Rated Power; (c) Station Production Rate; (d) Initial Station Reliability; (e) Buffer Fill Percentage; and (f) Number of Maintenance Resources
The following observations can be made from the plots:

- As $RP_i$ increases $C_{part}$ increases.

- The overall trend for $C_{part}$ is increasing as $MP_i$ increases. However, the marginal change in $C_{part}$ is not very significant.

- For $PR_i$ and $r_i(t=1)$, as they increase, $C_{part}$ decreases dramatically.

- $C_{part}$ follows a decreasing trend as $BU_{i(t=1)}$ increases from $\sim 10\%$ to $\sim 80\%$. When $BU_{i(t=1)}$ is at $0\%$ or above $90\%$ the harmful effects of blockage and starvation are reflected in the cost per part.

- The relationship between $C_{part}$ and $MCr$ seems to be nonlinear however, it only results in very little fluctuation on the cost per part.

A comparison of $C_{part}$ is summarized in Table 3.11.

**Table 3.11 Range of $C_{part}$ for Different Parameters**

<table>
<thead>
<tr>
<th>Factor</th>
<th>$C_{part}$ ($/part)$</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>$RP_i$</td>
<td>2.05</td>
<td>1.39</td>
</tr>
<tr>
<td>$MP_i$</td>
<td>1.63</td>
<td>1.56</td>
</tr>
<tr>
<td>$PR_i$</td>
<td>3.19</td>
<td>0.016</td>
</tr>
<tr>
<td>$r_i(t=1)$</td>
<td>2.07</td>
<td>1.58</td>
</tr>
<tr>
<td>$BU_{i(t=1)}$</td>
<td>2.48</td>
<td>1.32</td>
</tr>
<tr>
<td>$MCr$</td>
<td>1.66</td>
<td>1.598</td>
</tr>
</tbody>
</table>
The production rate, \( PR_i \), and the rated power, \( RP_i \), of the stations have the broadest range of values for \( C_{\text{part}} \). Furthermore, \( MP_i \) and \( MC_r \) are the parameters having the lowest range of values for \( C_{\text{part}} \). The production rate of the stations \( PR_i \) brings the most substantial change observed for \( C_{\text{part}} \). Additionally, \( PR_i \) of the stations has a range for \( C_{\text{part}} \), from a rise by 100.6% to a reduction of 98.99% (This reduction, though being numerically observed and tested, may not be physically feasible in reality).
3.3 Multifactor Analysis

In this section, the effect of the several key factors considered in the joint energy and maintenance production planning problem are analyzed by changing the factors’ levels over a sample consisting of numerous schedules of production. Design of Experiments (DOE) methodology is used. The system parameters/factors are the same as those from the one-factor-at-a-time analysis in the previous subsection.

Using the PSO, different solutions of the scheduling problem will be obtained each time the algorithm is implemented. For the proposed methodology to be robust, different samples of production and maintenance schedules (based on the proposed scheduling problem) are needed. Thus, simulation sampling procedures to produce different operation schedules for each parameter setting are utilized. In this study, Monte Carlo sampling approach is used. The four steps associated with this approach are (Sheehy and Martz, 2012): (1) the transfer equation is needed (the transfer equation will be the joint energy and maintenance production scheduling model); (2) the input parameters that needs to be generated need to be defined (the stations’ “on/off” states and the maintenance schedule throughout the production horizon); (3) the dataset needs to be simulated (the PSO method will be used to generate the dataset); and (4) the data needs to be analyzed (DOE methodology will be used to analyze the data).

The experiment considers a $3^6$ factorial design with 32 replications for which 32 schedules are generated. The evaluation of 32 sample schedules is done on the combinations of $3^6$ factor design. The resulting cost per part under the $3^6$ factor combinations for the PSO obtained schedules is graphically represented in Figure 3.4. Also, a boxplot for the cost per part under these $3^6$ factor combinations is shown in Figure 3.5. Finally, the factors and factor levels are shown in Table 3.12.
### Table 3.12 Factor Levels

<table>
<thead>
<tr>
<th>Factors</th>
<th>Levels</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$RP_i$</td>
<td></td>
<td>0.8</td>
<td>1.15</td>
<td>1.5</td>
</tr>
<tr>
<td>$MP_i$</td>
<td></td>
<td>0.8</td>
<td>1.15</td>
<td>1.5</td>
</tr>
<tr>
<td>$PR_i$</td>
<td></td>
<td>40</td>
<td>55</td>
<td>70</td>
</tr>
<tr>
<td>$r_{i(t=1)}$</td>
<td></td>
<td>0.7</td>
<td>0.8</td>
<td>0.9</td>
</tr>
<tr>
<td>$BU_{i(t=1)}$</td>
<td></td>
<td>0</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>$MCr$</td>
<td></td>
<td>1</td>
<td>3</td>
<td>5</td>
</tr>
</tbody>
</table>

**Figure 3.4** $C_{part}$ for PSO Generated Samples
A 3-level full factorial analysis using ANOVA is conducted and the results are obtained. It is observed that the maintenance power consumption, \( MP_i \), is insignificant. Additionally, interactions higher than 2nd order are not significant. Thus, \( MP_i \) and all interactions over 2nd order are removed. In Figure 3.6 and Table 3.13, the interaction plot and ANOVA output table obtained are presented, respectively. Furthermore, the normal probability plot and histogram of the residuals are presented in Figure 3.7.

### Table 3.13 Reduced ANOVA Table

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Adj SS</th>
<th>Adj MS</th>
<th>F-Value</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>50</td>
<td>50275.6</td>
<td>1005.5</td>
<td>11715.25</td>
<td>0.000</td>
</tr>
<tr>
<td>Linear</td>
<td>10</td>
<td>49721.6</td>
<td>4972.2</td>
<td>57930.87</td>
<td>0.000</td>
</tr>
<tr>
<td>( P )</td>
<td>2</td>
<td>3082.7</td>
<td>1541.3</td>
<td>17958.08</td>
<td>0.000</td>
</tr>
<tr>
<td>PR</td>
<td>2</td>
<td>43156.9</td>
<td>21578.5</td>
<td>251411.70</td>
<td>0.000</td>
</tr>
<tr>
<td>RELint</td>
<td>2</td>
<td>2313.9</td>
<td>1156.9</td>
<td>13479.61</td>
<td>0.000</td>
</tr>
<tr>
<td>BU1</td>
<td>2</td>
<td>1139.1</td>
<td>569.6</td>
<td>6636.13</td>
<td>0.000</td>
</tr>
<tr>
<td>MC</td>
<td>2</td>
<td>29.0</td>
<td>14.5</td>
<td>168.82</td>
<td>0.000</td>
</tr>
<tr>
<td>2-Way Interactions</td>
<td>Df</td>
<td>Sum Sq</td>
<td>Mean Sq</td>
<td>F value</td>
<td>Pr(&gt;F)</td>
</tr>
<tr>
<td>--------------------</td>
<td>----</td>
<td>--------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>P*PR</td>
<td>4</td>
<td>164.7</td>
<td>41.2</td>
<td>479.78</td>
<td>0.000</td>
</tr>
<tr>
<td>P*RELint</td>
<td>4</td>
<td>6.8</td>
<td>1.7</td>
<td>19.86</td>
<td>0.000</td>
</tr>
<tr>
<td>P*BU1</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1.000</td>
</tr>
<tr>
<td>PR*RELint</td>
<td>4</td>
<td>365.0</td>
<td>91.2</td>
<td>1063.12</td>
<td>0.000</td>
</tr>
<tr>
<td>PR*BU1</td>
<td>4</td>
<td>13.8</td>
<td>3.5</td>
<td>40.30</td>
<td>0.000</td>
</tr>
<tr>
<td>PR*MC</td>
<td>4</td>
<td>1.5</td>
<td>0.4</td>
<td>4.51</td>
<td>0.001</td>
</tr>
<tr>
<td>RELint*BU1</td>
<td>4</td>
<td>1.0</td>
<td>0.3</td>
<td>3.03</td>
<td>0.016</td>
</tr>
<tr>
<td>RELint*MC</td>
<td>4</td>
<td>1.0</td>
<td>0.2</td>
<td>2.90</td>
<td>0.020</td>
</tr>
<tr>
<td>BU1*MC</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1.000</td>
</tr>
</tbody>
</table>

R-sq | R-sq(adj) | R-sq(pred)
96.18% | 96.17% | 96.16%

Figure 3.6 Main Effects Plot

A gray background represents a term not in the model.
Figure 3.7 Normal Probability Plot and Histogram of Residuals for ANOVA Analysis
3.4 Parameter Optimization

The predicted responses of the DOE factorial model can be affected by different experimental settings. Optimizing some specified set of parameters by adjusting the process, without violating the constraints, can help to minimize the overall operational cost (Montgomery, 1991). In Section 3.4.1, $C_{par}$ for the model in Scenario III is minimized to obtain optimal factor settings using Response Surface (RS) methodology. The results are further compared in Section 3.4.2 with the results of parameter optimization applied to baseline models in Scenarios I and II.

3.4.1 Effect of Parameter Optimization for Scenario III

A response surface (RS) model with quadratic terms is used. The results on the most significant factors and their interactions are similar to those gained in the factorial analysis. It is observed that $MP_i$ and all terms over 2 levels are insignificant. Also, the response surface plots for the factors and holding values are shown in Figure 3.8.

![Figure 3.8 Response Surface Plot](image-url)
To acquire the optimal factor settings, $C_{part}$ is minimized as shown in (24) using Response Surface (RS) methodology.

$$\min_{RP_i, PR_i, BU_i^{(t=0)}, r_i^{(t=0)}, MCr} \left( C_{part} \right)$$

(24)

The results shown in Figure 3.9 suggest that the minimum rated power and the maximum production rate are optimal. On the other hand, the maintenance resources, the initial station reliability, and the initial buffer content level fall into the mid-range. The corresponding normal probability plot and the histogram of residuals for the RS model are shown in Figure 3.10.

![Figure 3.9 Response Optimizer for Scenario III](image)

Using the RS approach, 69% reduction in $C_{part}$ is achieved with the rated power at 80%, production rate at 70, initial station reliabilities at 0.85, initial buffer contents at 0.69, and the maintenance resources at 3.
In all, the insights obtained are as follows:

- High initial station reliability combined with very high rate of production can lead to an excess production of parts and cause buffer blockage or incur holding costs.
- Optimal level of initial buffer is obtained at 68% of the average buffer capacities. Though, having too many parts on hand for the production line seem to be helpful, it can often lead to blockage and interrupt system stability if there are too many parts in the buffers.
- It is essential to balance the advantage of having the maintenance action being performed with the maintenance cost being incurred. Very few maintenance resources lead to rapidly degrading station reliability and production loss, too many maintenance resources and maintenance activity leads to unnecessary excess costs.
3.4.2 Effect of Parameter Optimization for Scenarios I and II

Again, $C_{part}$ is minimized as shown in (24) using RS methodology to obtain the optimal factor settings for Scenarios I and II as shown in Figure 3.11 and Figure 3.12. The results suggest that near the minimum rated power and the maximum production rate, initial reliability and maintenance resources, the responses are optimal. Meanwhile, the initial buffer content level fall into the mid-range.

![Figure 3.11 Response Optimizer for Scenario 1](image1)

![Figure 3.12 Response Optimizer for Scenario 2](image2)
Further, Table 3.14 shows the percentage savings obtained for the cost per part by performing parameter optimization after energy and maintenance scheduling. Using the RS approach, a reduction of 35.48 % and 20.07 % in $C_{part}$ is achieved for Scenario I and II respectively. On the other hand, Scenario III can attain savings of up to 69.55 % in $C_{part}$ after parameter optimization using the RS approach. These savings are achieved under the assumption that no physical restrictions are considered.

The RS approach for the baseline Scenarios I and II, where PSO optimized energy and maintenance schedules are not considered, achieves around 20 to 35 % of savings in $C_{part}$. When the proposed energy and maintenance schedule is considered (Scenario III), an additional 42 to 55 % savings in $C_{part}$ is achieved as shown in Table 3.15. This justifies the need of optimizing energy and maintenance schedules together with parameter optimization by integrating the proposed joint model with the DOE model. This will ensure that maximum reduction in $C_{part}$ is achieved.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Cost per part ($)</th>
<th>Percentage savings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without parameter optimization</td>
<td>With parameter optimization</td>
</tr>
<tr>
<td>I</td>
<td>2.205</td>
<td>1.4225</td>
</tr>
<tr>
<td>II</td>
<td>1.989</td>
<td>1.5899</td>
</tr>
<tr>
<td>III</td>
<td>1.599</td>
<td>0.4869</td>
</tr>
</tbody>
</table>
Table 3.15 Additional Percentage Savings for Cost Per Part Compared to Proposed Joint Model with Parameter Optimization

<table>
<thead>
<tr>
<th>Comparison between scenarios</th>
<th>Additional percentage savings</th>
</tr>
</thead>
<tbody>
<tr>
<td>III vs I</td>
<td>42.44%</td>
</tr>
<tr>
<td>III vs II</td>
<td>55.45%</td>
</tr>
</tbody>
</table>
4 PARTICLE SWARM OPTIMIZATION

The need to use metaheuristic methods for solving the proposed joint energy and maintenance production planning problem is recognized because of its ability to find good solutions in an affordable time. One such local search metaheuristic algorithm to generate an optimal schedule for the proposed problem is Particle Swarm Optimization (PSO). The PSO mechanism is encouraged by the swarming and collaborative behavior of biological populations (Hassan et al., 2005). The PSO proposed is modified by adding strategies like local optimal avoidable strategy and time varying inertia weight to improve the computational capability of the PSO to arrive at an optimal solution. Extensive numerical results of the modified PSO method are presented in Section 4.2.
4.1 Modified PSO Algorithm

Particle swarm optimization is used to arrive at the near optimal production and maintenance schedule for the proposed joint model. Using PSO, a population of possible solutions is generated, called a swarm. The PSO model is described as follows. Each swarm particle in the model has a dimension of $(M+M) \times J$, where the schedule for energy control of a $M$-station-$M$-1-buffer manufacturing system is given by the first $M \times J$ sub matrix. The schedule for maintenance is given by the second $M \times J$ sub matrix. The planning horizon comprises of $J$ intervals.

The first sub-matrix will store all $e_{it}$, while the second sub-matrix shall store all $m_{it}$. The velocity update equation then enables the particles to fly towards the better position in the searching space over time. To avoid any premature convergence and enhancing the exploration capability, the thesis adapts the local optimal avoidable strategy (Salehizadeh et al., 2009). In addition, a time varying inertial weight (Blondin, 2009) has also been adopted for the PSO methodology.

The whole swarm is separated into two populations based on avoidance rate, $\gamma(s)$, which can be determined iteratively using (25).

\[
\gamma(s) = \begin{cases} 
\text{rand}(0,1), & \text{if } s < 0.75 \times s_{\text{max}} \\
1, & \text{otherwise}
\end{cases}
\] (25)

Eventually, the expression $p = \text{round} \left( P' \times \gamma(s) \right)$ denotes the number of particles that perform the standard PSO with inertia weight, which update their velocities according to equation (26). And, $P' - p$ denotes the number of particles that perform local optimal avoidable PSO, which update their velocities according to equation (27).
The time varying inertial weight is denoted by $\alpha(s)$ at iteration $s$. The value for $\alpha(s)$ is confined within the minimum ($\alpha_{\text{min}}$) and maximum ($\alpha_{\text{max}}$) inertial weight values. Starting at the maximum value in the first iteration, the inertial weight gradually reduces, with each iteration, to the minimum value in the final iteration according to equation (28).

$$\alpha(s) = \alpha_{\text{max}} - \left( \frac{\alpha_{\text{max}} - \alpha_{\text{min}}}{s_{\text{max}}} \right) s$$ (28)

The search for optimal solution is more global with higher inertial weight. Eventually, a more localized search is performed to find the optimal solution as the inertial weight decreases.

$l(s)$ in (26) is defined as “avoidance coefficient”, which is updated iteratively according to expression (29)

$$l(s) = 2 \left( 1 - \frac{s}{s_{\text{max}}} \right)$$ (29)

Finally, the position for all the particles from both the populations is updated according to expression (30)

$$L_o(s+1) = L_o(s) + V_o(s+1), \text{ where } o \in \{1, 2, \ldots, P^*\}$$ (30)
The initialized first sub-matrix (energy control) has an assignment by value one for all of its $N \times T$ elements. Due to constraint (4), the number of feasible solutions may significantly reduce when a number is randomly drawn from the set \{0,1\} to initiate the first sub-matrix. Similarly, the second sub-matrix (maintenance planning) has an assignment by value zero for all of its $N \times T$ elements. Constraint (5) ensures that the number of feasible solutions shall significantly reduce unless zero is used to initialize.

The initial velocity of each particle, $V(s=1)$, for both the sub-matrices is produced randomly from the set \{-1, 0, 1\}. Since both $V$ and $L$ are updated using real numbers for the energy control sub-matrix as well as the maintenance planning sub-matrix, additional steps as shown in formulations (31) and (32) are needed to further update $V$ and $L$ such that they lie in the set \{-1, 0, 1\} and the set \{0, 1\}, respectively (Wang and Li, 2013). Figure 4.1 summarizes the PSO procedure used to solve the proposed scheduling model.

\[
V(s+1) = \begin{cases} 
-1, & \text{if } V(s+1) < -0.5 \\
0, & \text{if } -0.5 \leq V(s+1) \leq 0.5 \\
1, & \text{if } V(s+1) > 0.5 
\end{cases} \quad (31)
\]

\[
L(s+1) = \begin{cases} 
L(s)+V(s+1), & \text{if } 0 \leq L(s)+V(s+1) \leq 1 \\
0, & \text{if } L(s)+V(s+1) < 0 \\
1, & \text{if } L(s)+V(s+1) > 1 
\end{cases} \quad (32)
\]
Figure 4.1 Solution Procedure using Standard and Local Optimal Avoidable PSOs with Time Varying Inertia Weight
4.2 Numerical Results

Various numerical experiments are performed on the proposed joint energy, maintenance and production planning model using the modified PSO algorithm. In the following sub sections, the numerical results on parameter tuning of modified PSO, comparison with other approaches such as Standard PSO and GA, and testing the modified PSO for system size are presented.

4.2.1 Parameter Tuning for Modified PSO

The computational behavior of PSO is significantly affected by its parameters (Rezaee and Jasni, 2013). So, the way of tuning the parameters which can attain a desirable computational behavior, is of high importance. While some parameters are determined through literature, others are attained through parameter tuning. However, these do not guarantee global optimal solution. The numerical results concerning the choice of inertia weight ($\alpha$) and learning factors ($c_1$ and $c_2$) are presented in sections 4.2.1.1 and 4.2.1.2.

4.2.1.1 Selection of Inertia Weight parameter, $\alpha$

The inertia weight can be considered to represent the fluidity of the medium in which a particle moves. Various existent literature (Bansal et al., 2011; Blondin, 2009; Zhou and Shi, 2011), suggests the value for PSO inertia weight, $\alpha$, is typically chosen in the range [0.4, 0.9]. Global search is achieved by selecting a large inertia weight, whereas for local search, a small inertia weight is a better option. Setting the inertia weight to a relatively high initial value (e.g., 0.9) allows the particles to move easily and perform extensive exploration in a low viscosity medium. Gradually reducing the inertia weight to a lower value (e.g., 0.4) allows the particles to perform more exploitation in a high viscosity medium (Arasomwan and Adewumi, 2013).
The modified PSO described in Section 4.1 is tested for no inertia weight, constant inertia weight and linearly decreasing inertia weight. The results are also compared with the Standard PSO where no population split is considered. These results are shown in Table 4.1 where the total cost ($) of the proposed joint model is tested for different inertia weight configurations of PSO.

Table 4.1 Total Cost ($) due to Different Inertia Weight Configurations of PSO

<table>
<thead>
<tr>
<th>Inertia Weight (( \alpha ))</th>
<th>PSO Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Value</td>
</tr>
<tr>
<td>No inertia weight</td>
<td>--</td>
</tr>
<tr>
<td>Constant inertia weight</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>0.4</td>
</tr>
<tr>
<td>Linearly decreasing inertia</td>
<td>0.9 to 0.4</td>
</tr>
</tbody>
</table>

*Tested using population size of 1000 over 100 iterations

Comparison of the results in Table 4.1 shows that PSO produces better solution quality when a linearly decreasing inertia weight is chosen. The gradual transition in the fluidity of the medium enhances particles’ exploration in the initial stages of search and exploitation in the final stages of search. The higher cost values in the cases with no inertia weight and constant inertia weight suggest premature convergence of PSO or the particles might have converged to a local optimum.
4.2.1.2 Selection of Acceleration Factors $c_1$ and $c_2$

The acceleration factor, $c_1$, also called the cognitive component, performs as the memory of the particle. It causes the particle to return to the search space regions where the particle has experienced high individual fitness. To improve system stability, the factor $c_1$ is set close to 2. This affects the step-size that the particle takes toward its corresponding best candidate solution (Blondin, 2009; Zhang et al., 2008; Zhou and Shi, 2011).

The acceleration factor, $c_2$, also called the social component, results in the particle moving towards the best region found by the swarm as of that time. The factor $c_2$ is also typically chosen close to 2. This represents the step-size that the particle takes towards its corresponding global best candidate solution. The factors $c_1$ and $c_2$ are tested over the range $[0, 2]$ using the modified PSO described in Section 4.1, and the results are also compared with standard PSO where no population split is considered. These results are shown in Table 4.2 where the total cost ($) of the proposed joint model is tested. It is seen that setting the accelerations factors to 2 allows the PSO to attain the lowest cost for the proposed joint model.

<table>
<thead>
<tr>
<th>Acceleration factors ($c_1$ &amp; $c_2$)</th>
<th>PSO Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No split</td>
</tr>
<tr>
<td>2</td>
<td>2,303.74</td>
</tr>
<tr>
<td>1.5</td>
<td>2,302.87</td>
</tr>
<tr>
<td>1</td>
<td>2,304.74</td>
</tr>
<tr>
<td>0.5</td>
<td>2,310.24</td>
</tr>
<tr>
<td>0</td>
<td>2,335.04</td>
</tr>
</tbody>
</table>

*Tested using population size of 1000 over 100 iterations
**Linearly decreasing inertial weight
4.2.2 Comparison of Standard PSO and Modified PSO

This analysis compares the standard PSO and the modified PSO to assess the efficiency of the added strategies in the modified PSO described in Section 4.1. The results of solution quality and computational time are compared over different number of iterations as shown in Table 4.3. The standard PSO is implemented using constant inertia weight and linearly decreasing inertia weight. A population size of 1000 is considered for the swarm. It is observed that better results are obtained when using the split population and varying inertial weight strategies simultaneously, as proposed in Section 4.1.

Table 4.3 Effectiveness of PSO using Proposed Strategies in Modified Joint Model

<table>
<thead>
<tr>
<th>No. of Iterations</th>
<th>Standard PSO with constant inertia weight</th>
<th>Standard PSO with linearly decreasing inertia weight</th>
<th>Modified PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Solution Quality ($), Computation Time (sec)</td>
<td>Solution Quality ($), Computation Time (sec)</td>
<td>Solution Quality ($), Computation Time (sec)</td>
</tr>
<tr>
<td>50</td>
<td>2,309.10, 268.47</td>
<td>2,305.46, 270.73</td>
<td>2,296.27, 260.34</td>
</tr>
<tr>
<td>100</td>
<td>2,308.30, 522.89</td>
<td>2,303.74, 519.29</td>
<td>2,254.61, 508.94</td>
</tr>
<tr>
<td>150</td>
<td>2,306.88, 802.27</td>
<td>2,304.57, 795.38</td>
<td>2,240.93, 800.29</td>
</tr>
<tr>
<td>200</td>
<td>2,305.24, 1075.09</td>
<td>2,304.88, 1078.74</td>
<td>2,167.25, 1,068.97</td>
</tr>
</tbody>
</table>
4.2.3 Comparison of PSO and GA

An alternate evolutionary heuristic to PSO is the population based search method called Genetic Algorithm (GA). GA is an evolutionary search procedure inspired by the biological mechanism which is based on the principles of natural genetics and selection (Chircu, 2010), which is popular in academia and industry. It is founded on the concept of survival of the fittest, to guide the search to select and generate individuals to adapt to the environment.

The optimization procedure using GA begins by generation of a random (partial or complete random) population of candidate solutions, called individuals, which are represented as chromosomes. Each individual is decoded into the decision variable domain to determine the fitness value that represents the individual’s performance. The GA then typically employs three operators; Selection, Crossover and Mutation to propagate the population towards better individuals from one generation to another and obtain a new population.

The Selection operator, based on the concept of survival of the fittest, selects the best individuals to become parents for the next generation. The Crossover operator performs mating of parents to generate new individuals thereby ensuring that best genetic materials are propagated further. The Mutation operator then promotes diversity in population characteristics which encourages global search of the solution space, thereby preventing the algorithm from getting trapped in local minima. The GA algorithm is summarized in Figure 4.2.
Figure 4.2 Genetic Algorithm Solution Procedure
The objective in this section is to compare the computational effectiveness and efficiency of the modified PSO algorithm with GA. For this study, a binary encoded GA is employed considering the joint energy and maintenance production scheduling problem.

First, the GA performance for different selection operators is tested as shown in the Table 4.4. A uniform crossover and a mutation rate of 0.02 is employed. The results of solution quality and computational time are compared over a range of iterations. It is observed that tournament selection turns out to be the best operator for selecting the best individuals for the proposed model.

<table>
<thead>
<tr>
<th>No. of Iterations</th>
<th>GA Selection Operators</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Roulette Wheel Selection</td>
</tr>
<tr>
<td></td>
<td>Solution Quality ($)</td>
</tr>
<tr>
<td>50</td>
<td>2,334.78</td>
</tr>
<tr>
<td>100</td>
<td>2,322.17</td>
</tr>
<tr>
<td>150</td>
<td>2,287.93</td>
</tr>
<tr>
<td>200</td>
<td>2,287.61</td>
</tr>
</tbody>
</table>

Further, to assess the computational efficiency, the results of the GA with the tournament selection operator are compared with the results of the modified PSO as shown in Table 4.5. The population size for both GA and PSO is set to 1,000. It is observed that the GA performs better than the Standard PSO when number of generations are high. However, the modified PSO
performs significantly better than the GA in terms of the solution quality obtained for a similar computational effort.

**Table 4.5 Comparison of Solution Quality of Modified PSO and GA**

<table>
<thead>
<tr>
<th>No. of Iterations</th>
<th>Genetic algorithm with Tournament Selection</th>
<th>Standard PSO with linearly decreasing inertia weight</th>
<th>Modified PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Solution Quality ($)</td>
<td>Computation Time (sec)</td>
<td>Solution Quality ($)</td>
</tr>
<tr>
<td>50</td>
<td>2,308.56</td>
<td>292.82</td>
<td>2,305.46</td>
</tr>
<tr>
<td>100</td>
<td>2,301.67</td>
<td>543.93</td>
<td>2,303.74</td>
</tr>
<tr>
<td>150</td>
<td>2,287.24</td>
<td>769.42</td>
<td>2,304.57</td>
</tr>
<tr>
<td>200</td>
<td>2,282.80</td>
<td>1,060.78</td>
<td>2,304.89</td>
</tr>
</tbody>
</table>

A numerical experiment for GA is also run by setting the population size to 3,000 and number of generations to 200. The experiment lasts nearly 2,300 seconds, but the solution quality obtained is only $2,279.63, which is significantly higher than the solution quality of $2,167.26 achieved by modified PSO in comparatively less computational effort. This suggests that the modified PSO algorithm allows a greater diversity and exploration compared to GA for the proposed joint model which results in it being more computationally efficient.
4.2.4 Testing the Modified PSO for Large System Sizes

To test the dimensional capability, the modified PSO for the proposed joint energy, maintenance and production planning model is analyzed for a 50-station system. This system includes a total of 8,000 decision variables (2×50 stations × 160 intervals). The number of maintenance crew resources, MCr, is set to 17 and the committed power limitation, PA, is set to 850 kW. The results suggest that the PSO is still able to arrive at a solution in a finite time. Increasing the swarm population size produces better solution quality, however, at the expense of an increased computational effort.

Table 4.6 PSO Results for a Larger System Size

<table>
<thead>
<tr>
<th>PSO Population Size</th>
<th>500</th>
<th>1000</th>
<th>2000</th>
<th>3000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Iterations</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td>Throughput</td>
<td>1,380</td>
<td>1,405</td>
<td>1,405</td>
<td>1,405</td>
</tr>
<tr>
<td>Electricity Cost ($)</td>
<td>3,534.32</td>
<td>3,533.21</td>
<td>3,476.25</td>
<td>3,532.31</td>
</tr>
<tr>
<td>Maintenance Cost ($)</td>
<td>5,329</td>
<td>5,243</td>
<td>5,173</td>
<td>5,238</td>
</tr>
<tr>
<td>Demand Charge ($)</td>
<td>15,898.61</td>
<td>15,716.8</td>
<td>15,843.43</td>
<td>15,510</td>
</tr>
<tr>
<td>Throughput Benefit/Penalty ($)</td>
<td>98.304</td>
<td>-16.014</td>
<td>-16.014</td>
<td>-16.014</td>
</tr>
<tr>
<td>Total Cost ($)</td>
<td>24,860.24</td>
<td>24,476.99</td>
<td>24,476.67</td>
<td>24,264.30</td>
</tr>
<tr>
<td>Time (seconds)</td>
<td>1,439.46</td>
<td>2,935.54</td>
<td>5,973.39</td>
<td>18,705.86</td>
</tr>
</tbody>
</table>
5 CONCLUSION AND FUTURE WORK

Methodology on integrated energy and maintenance production planning while considering production and physical constraints is presented, in which the scheduling problem and cost per part model are formulated. The goal of the proposed scheduling problem is to provide the manufacturer with an integrated energy and maintenance production scheduling tool. In addition, the unit cost model can be used to determine the actual system performance in case of discrepancies or desired changes in system parameter values. A factorial analysis is conducted, using both single factor and multifactor analysis, to study the sensitivity of the cost per part under variable system parameter conditions and different production schedules. Important insights on the factor interactions and optimal system parameter values are achieved.

The case study presents a comparison of three scheduling scenarios of the production scheduling model considering station degradation over time and a TOU electricity demand response program. Due to the high non-energy related maintenance cost from Scenarios I and II, the total cost for these scenarios is much higher than Scenario III. Also, Scenario III shows a savings of around 19 to 27 % in cost per part in comparison to the baseline Scenarios I and II.

The case study for the second model, displays around 20 to 35 % savings in cost per part for the baseline scenarios after optimizing key production system parameters. These savings are further illustrated from 42 to 55 % when the parameter optimization for the solved production follows the optimal scheduling procedure. The rated power from production, the production rate, and the initial machine reliabilities prove to be the most impactful parameters on the sensitivity of cost per part.

The modified Particle Swarm Optimization (PSO) algorithm presented and used, incorporates local optimal avoidable strategy and time varying inertia weight mechanisms. These
allowed greater diversity and exploration compared to the standard PSO and Genetic Algorithm (GA) for the proposed joint model. The modified PSO is shown to be more computationally efficient in determining the optimal scheduling; while GA is shown to lack such computational efficiency for the proposed problem. The numerical result shows that GA could achieve a solution quality of $2,279.63$ at an expense of $2,300$ seconds in computational effort. In comparison, the modified PSO algorithm achieves a solution quality of $2,167.26$ in $1,068.97$ seconds which is less than half the computational effort required by GA. The modified PSO also shows to be effective in solving larger size problems (a 50-station system is tested).

In the future, different production cycles and alternate sources of energy can be examined for the analysis of the presented methodology. Also, different energy efficiency and demand response programs, and various production line settings can be considered to further develop the proposed methodology. This work can also be advanced to include real-time joint energy and maintenance planning. Finally, the proposed solution algorithm can be made more flexible and robust by hybridizing with GA or other search procedures like Simulated Annealing. This may help resolve issues of premature convergence to local optima when a problem with very large solution space is considered. This may ensure better quality solutions with reasonable computational effort for real life scheduling problems.
REFERENCES


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