A Modified Firefly Algorithm for Global Optimization of Supply Chain Networks

Abdulhadi Altherwi
Department of Industrial Engineering
Jazan University
Jazan, Saudi Arabia
Department of Industrial & Systems Engineering
Oakland University
Rochester, MI 48309, USA
aaltherwi@oakland.edu

Mohamed Zohdy
Department of Electrical & Computer Engineering
Oakland University
Rochester, MI 48309, USA
zohdyma@oakland.edu

Richard Olawoyin
Department of Industrial & Systems Engineering
Oakland University
Rochester, MI 48309, USA
olawoyin@oakland.edu

Daw Alwerfalli
A. Leon Linton Department of Mechanical Engineering
Lawrence Technological University
Southfield, MI 48075, USA
dalwerfal@ltu.edu

Abstract

This paper explores the optimization of supply chain networks for industrial plants in the manufacturing sector under a vendor-managed inventory (VMI) policy. It puts more emphasis on the global coordination of multi-plant warehouses managed by vendors using the VMI policy that use Long Range Wide Area Network (LoRaWAN) technology, which aims to reduce the network's total cost and enhance customer service. The problem was initially developed as a mixed-integer non-linear program (MINLP) model. To achieve better results, the modified firefly algorithm using exploration and exploitation was employed to solve the problem. The simulation results indicated that the modified firefly algorithm has better outcomes for optimizing supply chain networks than the standard one. Additionally, the computational time was reduced using the proposed algorithm. Response surface methodology was applied to tune the parameters' algorithms and trained to test the validity of the model. A case study for pipes manufacturing integrated supply chain is used to demonstrate the efficiency of the model and the solutions obtained by the firefly algorithm.

Keywords
Firefly Algorithm, Supply Chain Networks, Vendor-Managed Inventory, LoRaWAN Technology

1. Introduction

1.1 Firefly Algorithm for Global Optimization

The firefly algorithm stands out among the best new bio-inspired optimization techniques introduced by Yang (Yang 2010). The firefly algorithm is considered one of the family members of the swarm intelligence algorithm, which has displayed significant performance in solving optimization issues. The central concept of the firefly algorithm is that the bioluminescence of insects could be used to communicate. The fireflies' flashing lights can warn fireflies of potential predators and attract mating other fireflies. An essential factor in the life of fireflies is their brightness and other applications. These applications range from warning predators to displaying their attractiveness to other fireflies. The amount of effectiveness versus predators and attractiveness adds value to others depending on the firefly's light intensity, the distance between other insects, and absorption by the atmosphere (Fister et al. 2015). Some characteristics of flashing lights of fireflies can design a firefly-inspired algorithm effectively by three idealized rules (Gupta and Padhy 2016; Yang 2010; Yang 2010):

1. All fireflies are unisex, so one firefly can attract others regardless of the sex.
2. The quality of solution is based on the brightness of fireflies, which is proportional to the objective function.
3. A firefly with less brightness will be moved toward the brighter one. Otherwise, it will move randomly if it is the brighter one.

For example, if firefly J is brighter than firefly I, then, the position after the movement of fireflies will be considered as follows:

$$x_i^{t+1} = x_i^t + \beta_0\left(x_j^t - x_i^t\right) + \alpha_i \varepsilon_i^t \tag{1}$$

Where $\beta = \beta_0 \exp(-\Upsilon r^2)$ is considered as the attractiveness, with β_0 indicating the attractiveness at distance r = 0, while the light absorption coefficient is Υ. Parameter $\boldsymbol{\varepsilon_i^t}$ is a vector of arbitrary numbers drawn from a Gaussian or uniform distribution at time t, and $\boldsymbol{\alpha_i}$ is a parameter controlling the progression measure (step size) which means the randomization parameter. Note that if β_0 is equal to zero, the movement of fireflies walk randomly. Equation (1) is summarized by the three parameters mentioned above, which are the parameter of randomization, attractiveness, and the third parameter is the coefficient of absorption. The firefly algorithm identifies two behaviors of asymptote:

- If Υ is very large, then the fireflies will be moved randomly according to Equation (1).
- If Υ goes to zero, the attractiveness will be constant, which results in $\beta = \beta_0$ during the search space.

Optimization is a common practice in daily decision making, hence creating a universal aspect of applicability of optimization as in this study. A rise in interest in biologically-based and evolutionary-based optimization algorithms has been witnessed in recent decades (Simon 2013). In this paper, we examine how global optimization problems can be solved using new variations of the biologically optimized algorithms.

Different optimization methods have been formulated to solve diverse and specific problems, and no one optimization approach can solve all problems. Accordingly, nontraditional optimization methods have also been introduced to solve complex engineering problems. Most complex engineering problems can be solved by popular and influential optimization techniques such as, Colony Optimization Algorithm (COA), fuzzy optimization, Genetic Algorithm (GA), and firefly algorithm (Talbi 2009). In the standard firefly algorithm (FA), there are different kinds of issues. These issues are light intensity, distance, movement, and attractiveness (Yang 2013). In optimization problems, one firefly represents a solution; the light intensity of a single firefly is always equivalent to solution quality (Yang, 2013). The first step is having an initial population of the firefly insects, *ergo* a random population. The second step is two fireflies (which means two solutions) are compared, then a firefly that does not shine as bright (a weaker solution) will always move toward the better solution (the bright firefly). All firefly positions are updated, and the steps are followed and continued until they are able to finish comparing all fireflies. After creating a new population of fireflies, the steps are redone on the new population of fireflies that they have created. They continue with this process until they are satisfied and stop that criterion (Gandomi et al. 2011). Figure 1 shows the Pseudo code of the standard firefly algorithm.

Algorithm 1: Pseudo code of the basic firefly algorithm for

Input: objective function $f(x_i)$, generate population of fireflies $x = (x_1, x_2, \ldots, x_N)$;
Output: find the best solution;
While (t < Max Generation)
$\boldsymbol{For\ i = 1:N}$
$\boldsymbol{For\ j = 1:N}$
$\boldsymbol{If\ I_j > I_i}$
by using uniform distribution, move firefly i towards j;
evaluate new solution and update light intensity $f(x_i^{(t)})$;
rank fireflies and find the best;
$t = t + 1$;
End if
End for
End for i
End while
End

Figure 1. Pseudo code of standard firefly algorithm (Yang, 2010)

1.2 Integrating VMI Policy in Manufacturing Systems

In recent research, researchers tended to design integrated logistics and closed-loop supply chain (Govindan et al. 2015). According to Billington (1987), supply chain management is a competitive tool that has the capability of bringing advantages, which can foster improvement for long and short term operational performance. Due to the complexity of manufacturing systems, the supply chain approach can be a challenge in failing to match and satisfy all the demands, especially in situations where the size and location of the industrial plant is not considered, and there is no warehouse. The existing literature focuses on the investment of radio-frequency identification (RFID) technology for ordering and holding operations related to the inventory system (Li et al. 2016; Baysan and Ustundag 2013; Wu et al. 2009; Lee and Lee 2011). Beyond the literature focused on the investment of RFID technology in the inventory operations (Hung et al. 2016; Zhong et al. 2015), there has been still little research done on optimization of supply chain networks using LoRaWAN technology in the inventory operations related to manufacturing industries (Ben-Daya et al. 2019; Karampatzakis et al. 2019).

In this research, we applied the model in a different application using a meta-heuristic algorithm based on firefly algorithm to solve large-sized problems. Previous literature discussed that vendor used RFID as a perfect technology to reduce the total network cost. However, we expanded the research by considering LoRaWAN technology as a perfect technology. Additionally, we applied a modified firefly algorithm to the global optimization of supply chain networks with VMI in manufacturing systems with LoRaWAN technology investment. VMI is implemented by the vendor for the whole manufacturing network by combining the location of the storage facility with the allocation of the entire replenishment policy. The direct-delivery system is applied in industrial plants with no assigned warehouse, while the VMI policy is used for industrial plants with designated warehouses.

Long Range Wide Area Network (LoRaWAN) technology plays an essential role in minimizing cost of networks (Beliatis et al. 2018). The use of LoRaWAN in monitoring automated verifications and tracking is said to lead to cost reduction of both expired and defective items reaching the intended customers (Ogarkov 2019). Since LoRaWAN technology can reduce the cost, vendors adopt this technology with the aim of reducing the total network cost and enhancing the network's profitability (Beliatis et al. 2018). This research is based on the location-inventory problem with the investment level of LoRaWAN technology in the manufacturing field. The problem is developed as a mixed-integer non-linear program (MINLP) model to reduce the total supply network cost of a VMI supply chain network.

Figure 2 elaborates VMI's assignment and how manufacturing industries that applied VMI policy using LoRaWAN technology in the inventory systems can manage the collaboration between manufacturing plants with assigned warehouses and manufacturing plants without assigned warehouses. Additionally, this study is relatively engaged in researching inventory problems through the implementation of LoRaWAN technology. The modified firefly algorithm is employed for large-sized problems and for validation and verification. In addition, large-sized problems cannot be solved by commercial software; the modified firefly algorithm is used to address them in reasonable run time as shown in Table 4 . We applied the modified algorithm for small-and medium-sized problems to show the performance of the proposed algorithm when compared to the standard algorithm.

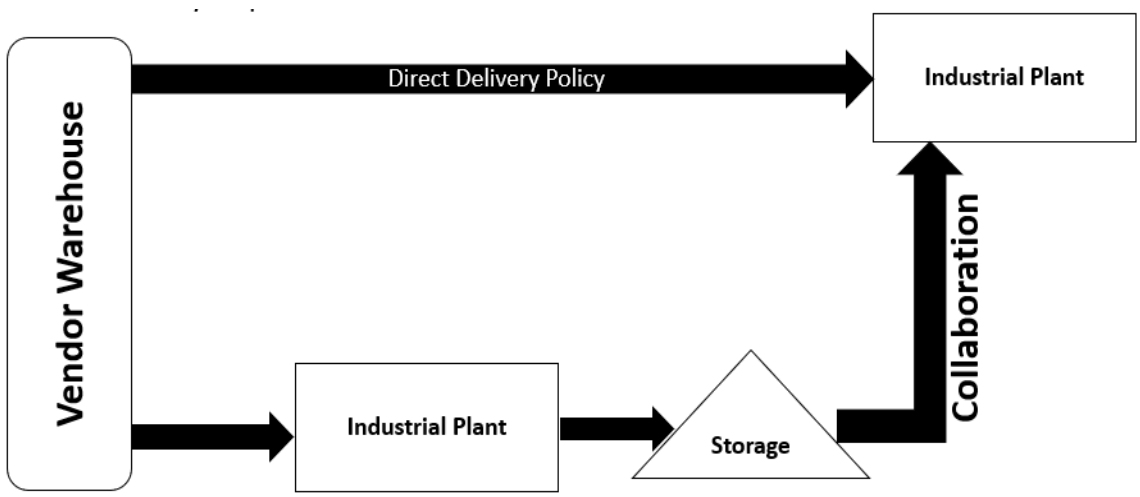

Figure 2. Assignment of VMI policy

2. The Modified Version of Firefly Algorithm

The firefly algorithm stands out among the best new bio-inspired optimization techniques. The modified firefly algorithm is introduced to solve supply network optimization problems. The need for modifying the algorithm is that the standard firefly algorithm has limitations. We implemented the standard firefly algorithm to compare it with the new modified version. The modified firefly algorithm is employed and used for validation and verification. The firefly algorithm is upgraded and can be sketched out in the pseudo-code, as shown in Figure 3. The mathematical articulation used to improve the movement of the firefly is done in Sababha et al. (2018). See Equation (2):

$$x_{i+1} = x_j + \beta(t)(x_i - x_j) + \alpha(t)\varepsilon_i \tag{2}$$

Where $\alpha(t)$ is the randomness coefficient at time t, ε_i is the random number, and $\beta(t)$ is the attractiveness coefficient at time t. x_i, x_j are the initial random population with less brightness (i) and more brightness (j). Sababha et al. (2018) considered this an exploitation technique represented by the first two terms to demonstrate a superior answer for the remainder of the operators while exploration procedures are depicted by the last term for inquiry space exploration in Equation (1). To enhance the precision of the algorithm of extraordinary worth, at that point, their movements should be focused on. Sababha et al. (2018) showed and expressed the randomness coefficient (α) in Equation (3) as:

$$\alpha(Itr_i) = \exp\left(1 - \left(\frac{Itr_{max}}{Itr_{max} - Itr_i}\right)^c\right) \tag{3}$$

C is considered as the whole or integer number to decide the speed of rotting of the irregularity, while Itr_{max} is considered as the maximum iteration number, and Itr_i is considered as the current number of iterations. In addition, parameter ϒ is a crucial viewpoint in describing the distinctions of the speed of the assembly and the attractiveness. The result is that when a steady (c) is connected in taking care of the issues of optimization, the firefly algorithm execution will be detectably obliged, as done in a customary firefly algorithm. Sababha et al. (2018) showed and expressed ϒ equation as follows:

$$\Upsilon(Itr_i) = 1 - \exp\left(1 - \left(\frac{Itr_{max}}{Itr_{max} - Itr_i}\right)^c\right) \tag{4}$$

Because of the modification, the proposed and modified firefly algorithm will not get caught in the neighborhood extraordinary, and it will heighten the combination speed, improving the arrangement at ideal a superior since there will be a balance among nearby and worldwide hunt. In the inquiry procedure, two refreshing formulas are clarified, picked arbitrarily, and introduced in equation (5) as done in Sababha et al. (2018):

$$\boldsymbol{x_{i+1}} = \begin{cases} \beta(i)x_i + x_j\big(1-\beta(i)\big) + \alpha(i)\varepsilon_i & rand > 0.5 \\ \dfrac{NG-i}{NG}(1-\delta)x_i + \delta x_{best} & Elsewhere \end{cases} \tag{5}$$

Parameter δ is considered as the gray coefficient, and NG is considered as the generation number. The fireflies can secure increasingly valuable data from others and change the bearings of light adaptively. At the last point, the progression estimation is intended to cause the algorithm to have a balance between exploitation and exploration procedures and to improve the algorithm on the off chance that the pursuit conditions are in modern and plentiful space and high terms.

Algorithm: Pseudo code of the proposed firefly algorithm for supply chain optimization
Input: Objective Function $f(x)$, population of fireflies x_o, Maximum number of Iterations Itr_{max},
Output: find the best solution;
ϒ which is light absorption coefficient, and α which is the randomness coefficient.
Create initial random population x_i, generate the light force I_0 at x_i by $f(x_i)$.
Do $Itr_i \leq Itr_{max}$
Consider the value of α and ϒ mentioned in equations (3) and (4) respectively
For loop i = 1 to N
For inner loop j = 1 to N
Evaluate the distance, r, between the two particles (x_j, x_i)
Consider the attractiveness $\beta = \exp(-\Upsilon r^2)$
If $\boldsymbol{I_j} > \boldsymbol{I_i}$, using uniform distribution, move firefly i towards j;
Update parameter values of α and ϒ as in equations (3) and (4) respectively
Consider new result for x_{i+1} as in equation (5)
End if
End for i
End for j
Update light intensity I_x
Rank the fireflies and find the best;
End while
end

Figure 3. Pseudo code for modified firefly algorithm (Sababha et al. 2018)

3. Problem Statement and Mathematical Formulation

3.1 Problem Definition

VMI policy is implemented by the vendor for the whole manufacturing network by combining the location-inventory assignment with the allocation of the entire replenishment policy. In this research, we consider the vendor implements two policies for the supply of goods, direct-delivery policy and VMI policy under demand uncertainty. The role of the vendor is to be focused on the inventory level to overcome the expected shortage that may occur at the industrial plants without warehouses. Once shortages occur, the industrial plants with assigned warehouses collaborate with industrial plants without warehouses under VMI policy. The direct-delivery system is applied in industrial plants with no assigned warehouse as a non-collaborative strategy, while the VMI policy is used for industrial plants with designated warehouses as a collaborative strategy. The vendor also applies a direct-delivery policy for the supply of goods to customers by courier. Parameters, indexes, and decision variables are presented in Table 1. The assumptions of Mixed Integer Non-Linear Programming (MINLP) Model are as follows:

- It assumed that each industrial plant with assigned warehouse can collaborate with industrial plants without assigned warehouses.
- The demand of all industrial plants for products is deterministic.
- We used a continuous review policy for VMI policy.
- The direct delivery cost to the manufacturing plants without assigned warehouses will be paid by the sender.
- All manufacturing plants support the same products and apply the VMI policy for their inventories.

Table 1. Indexes, notations, and decision variables used in this paper

Indexes	**Notations**
$\boldsymbol{i}, \boldsymbol{j}$, **k, l** indices for plants, products, vendors, and retailers respectively	$\boldsymbol{TC_{ij}}$ The cost of transportation of product j delivered to plant i. $\boldsymbol{OC_{ij}}$ The ordering cost per order $\boldsymbol{V_i}$ The volume of item per product i **bigM** very large number. $\boldsymbol{A_h}$ The minimum level of LoRaWAN investment to improve the efficiency of holding at the allocated warehouse. $\boldsymbol{A_o}$ The minimum level of LoRaWAN investment to improve the efficiency of ordering at the allocated warehouse. **μ** Exponential for the efficiency of holding. **β** Exponential for the efficiency of ordering. **C** There is no investment in LoRaWAN technology if lowest of efficiency of holding is achieved. **F** There is no investment in LoRaWAN technology if the lowest efficiency of ordering is achieved. **G** The highest level of efficiency of ordering which is achieved by L_{oi} investment in LoRaWAN technology. **M** The highest level of efficiency of holding which is achieved by L_{hi} investment in LoRaWAN technology. $\boldsymbol{S_{ij}}$ The minimum level of safety stock for product j at the plant i. $\boldsymbol{D_k}$ The vendor's demand rate $\boldsymbol{OC_l}$ The ordering cost of retailer from vendor $\boldsymbol{TC_l}$ The cost of transportation for orders to retailers
Decisions Variables $\boldsymbol{Z_{ij}}$ The number of order quantity of product j delivered to plant i with allocated warehouse. $(\boldsymbol{NS})_{\boldsymbol{i}}$ The number of shipments to plant i with allocated warehouse. $\boldsymbol{L_{ij}}$ Safety stock level at the plant i with allocated warehouse for j product. $\boldsymbol{P_{dl}}$ 1 if shipment for vendor is delivered directly to retailers, otherwise 0 $\boldsymbol{P_{wi}}$ 1 if vendor set a warehouse facility for product, otherwise 0 $\boldsymbol{L_{oi}}$ Level of LoRaWAN investment for efficiency of ordering for plant i with the allocated warehouse. $(\boldsymbol{OE})_{\boldsymbol{i}}$ The degree of the ordering cost is reduced by LoRaWAN investment L_{oi} at the plant i based on the efficiency of ordering $(\boldsymbol{HE})_{\boldsymbol{i}}$ The degree of the holding cost is reduced by LoRaWAN investment L_{hi} at the plant i based on the efficiency of holding. $\boldsymbol{K_{oi}}$ 1 if LoRaWAN technology is installed for the efficiency of ordering at the assigned warehouse. $\boldsymbol{K_{hi}}$ 1 if LoRaWAN technology is installed for the efficiency of holding at the assigned warehouse. $\boldsymbol{L_{hi}}$ Level of LoRaWAN investment for efficiency of holding for plant i with the allocated warehouse. $\boldsymbol{Q_k}$ Retailer's order quantity from vendor	

3.2 Mathematical Modeling

3.2.1 Mathematical Modeling of Scenario 1

Scenario 1 is the investment of LoRaWAN technology only in ordering operations. The objective function of each scenario is to minimize cost for a VMI supply network. The objective function of scenario 1 is determined in Equation (6). All related input parameters are defined in Table 1.

$$\boldsymbol{Min} \sum_{i=1}^{n}\sum_{j=1}^{m}(TC_{ij}+OC_{ij})R_{ij}P_{dl}+\sum_{k=1}^{v}\sum_{l=1}^{r}\frac{D_k}{Q_k}(TC_l+OC_l)+\sum_{i=1}^{n}\sum_{j=1}^{m}HC_{ij}\left(\frac{Z_{ij}}{2}+L_{ij}\right) + \sum_{i=1}^{n}SC_iP_{wi}+\sum_{i=1}^{n}L_{oi} \tag{6}$$

S.T

$$\sum_{j=1}^{m}(Z_{ij})\,V_i \le P_{wi}SS_i \qquad for\ \forall\ i=1,2,\dots\dots,n \quad and\ j=1,2,\dots.,m \tag{7}$$

$$\sum_{k=1}^{v} Q_{kl} \leq P_{wi} \qquad for\ \forall\ j = 1,2,..,m \quad and \quad i = 1,2,..n \tag{8}$$

$$OE_i = \left((G+F)(1-e^{-\beta L_{oi}})\right)P_{wi} \qquad for\ \forall\ i = 1,2,\ldots..,n \tag{9}$$

$$\mathrm{L_{oi}} \geq \mathrm{K_{oi}A_o} \qquad \text{for } \forall\ \mathrm{i} = 1,2,\ldots,\mathrm{n} \tag{10}$$

$$Z_{ij} \leq P_{wi} \tag{11}$$

$$P_{di} + P_{wi} = 1 \quad for\ \forall\ i = 1,2,\ldots,n \tag{12}$$

$$L_{ij} = P_{wi}S_{ij} \qquad for\ \forall\ i = 1,2,\ldots,n \quad and\ j = 1,2,\ldots,m \tag{13}$$

$$\sum_{j=1}^{m} Z_{ij} \leq CA_{Tr} \qquad for\ \forall\ i\ = 1,2,\ldots,n \tag{14}$$

$$NS_i \geq R_{ij}P_{wi} \qquad for\ \forall\ i = 1,2,..,n \quad and\ j = 1,2,..,m \tag{15}$$

$$L_{oi} \leq K_{oi} \qquad for\ \forall\ i = 1,2,\ldots,n \tag{16}$$

$$L_{oi} \leq P_{wi} \qquad for\ \forall\ i = 1,2,\ldots,n \tag{17}$$

$$K_{oi} \leq P_{wi} \qquad for\ \forall\ i = 1,2,\ldots\ldots,n \tag{18}$$

$$\mathrm{P_{di}, P_{wi}, K_{oi}} \in [0,1] \tag{19}$$

$$Z_{ij}, NS_i, L_{oi}, L_{ij} \geq 0 \qquad for\ \forall\ i = 1,2,\ldots,n \quad and\ j = 1,2,\ldots..,m \tag{20}$$

The first term stands for the courier transportation delivery costs per item for all demanded products and each plant with no designated warehouse. The second term indicates the ordering cost of retailer and the cost of transportation for orders delivered from vendor to retailer under direct delivery policy. The third term stands for summation of average order quality and the safety stock level for all the products at each industrial plant with designated warehouses. The fourth term stands for the sum of total costs of the fixed cost of setting up the warehouses at each industrial plant, as well as the rental cost for the assigned space by each plant for vendor warehousing purposes. The fifth term stands for LoRaWAN ordering investment costs for each plant with designated warehouses. See Equation (6).

Equation
(7) indicates that the safety stock level for products and the total size of order quantities per order should be equal to or less than the designated area for each industrial plant of *i* with designated warehouse while Equation
(8) indicates that each order of quantity of retailer from vendor should be determined if the vendor set a warehouse for products at the industrial plant. Equation (9) represents that the level of efficiency of ordering operations can be

a function of investment level in LoRaWAN technology for ordering operation (L_{oi}) L_{Oi}. A lower value of the efficiency of ordering operations represents a higher value of efficiency (Billington 1987). Equation (10) states that the minimum level of investment in LoRaWAN technology to improve the efficiency of ordering operations is greater than or equal to a minimum level of investment in LoRaWAN for A_o.

A lower value of the efficiency of holding operations represents a higher value of efficiency (Lee 2010). Equation (11) indicates that each order of quantity for products should be less than or equal to the value of bigM for plant i with allocated warehouse while equation (12) shows that each plant i could have a warehouse with vendor managed inventory (VMI) delivery or direct delivery with no allocated warehouse. Equation (13) states that the lower bound level of safety stock is limited and equal to the minimum value represented by S_{ij} for plants i with the allocated warehouse.

The constraint of the space of the truck is shown in Equation
(14). It states that the total size of order quantities for all products delivered to plant i with allocated warehouses is less than or equal to the truck's capacity. Equation (15) is the constraint of demand satisfaction. It states that the total number of order quantity of product j delivered to the plant i with allocated warehouse is greater than or equal to the demand of product j of plant i with allocated warehouse. Equation (16) represents the investment level in LoRaWAN in the efficiency of ordering operations should be less than or equal to bigM value. The maximum value of investment level in LoRaWAN for ordering at the plant i with allocated warehouse should be less than or equal to the value of bigM as presented in (17). The minimum investment level in LoRaWAN for improving the efficiency of ordering operations is applied at the assigned warehouse at the plant i as shown in (18). Equation (19) represents the binary constraint. All decision variables in the model should be non-negative values for validation, as shown in Equation (20).

3.2.2 The Mathematical Modeling of Scenario 2

Scenario 2 is the investment of LoRaWAN technology only in holding operations. The objective function of each scenario is to minimize cost for a VMI supply network. This objective function of scenario 2 is determined in Equation (21). All related input parameters are defined in Table 1.

$$Min \sum_{i=1}^{n}\sum_{j=1}^{m}(TC_{ij}+OC_{ij})R_{ij}P_{dl}+\sum_{k=1}^{v}\sum_{l=1}^{r}\frac{D_k}{Q_k}\,(TC_l+OC_l)+\sum_{i=1}^{n}\sum_{j=1}^{m}HE_i\,HC_{ij}(\frac{Z_{ij}}{2}+L_{ij}) + \sum_{i=1}^{n}SC_iP_{wi}+\sum_{i=1}^{n}L_{hi} \tag{21}$$

In addition to constraint

(8) and constraints (10)-(15) of scenario 1, we added constraints (22)-(28) for scenario 2.

$$HE_i = ((M+C)(1-e^{-\mu L_{hi}}))\,P_{wi} \qquad for\ \forall\ i = 1,2,\dots,n \tag{22}$$

$$L_{hi} \le P_{wi} \qquad for\ \forall\ i = 1,2,\dots,n \tag{23}$$

$$L_{hi} \le K_{hi} \quad for\ \forall\ i = 1,2,\dots,n \tag{24}$$

$$K_{hi} \le P_{wi} \quad for\ \forall\ i = 1,2,\dots,n \tag{25}$$

$$L_{hi} \ge K_{hi}A_h \qquad for\ \forall\ i = 1,2,\dots\dots..,n \tag{26}$$

$$P_{di}, P_{wi}, K_{hi} \in [0,1] \tag{27}$$

$$Z_{ij}, NS_i, L_{hi}, L_{ij} \geq 0 \qquad for\ \forall\ i = 1,2, \dots, n \quad and\ j = 1,2, \dots., m \tag{28}$$

The first term stands for the courier transportation delivery costs per item for all demanded products and each plant with no designated warehouse. The second term indicates the ordering cost of retailer and the cost of transportation for orders delivered from vendor to retailer under direct delivery policy. The third term stands for holding cost per item of the added average order quality and the safety stock level for all the products at each industrial plant with designated warehouses. The fourth term stands for the sum of total costs of the fixed cost of setting up the warehouses at each industrial plant as well as the rental cost for the assigned space by each plant for the vendor's warehousing purposes. The fifth term stands for LoRaWAN holding investment costs for each plant with designated warehouses. See Equation (21)

Equation (22) represents that the level of efficiency of ordering operations can be a function of investment level in LoRaWAN technology for ordering operation (L_{hi}) L_{hi}. Equation (23) shows that the maximum value of investment level in LoRaWAN technology for holding operations at plant i with allocated warehouse is less than or equal to the value of bigM. The investment level in LoRaWAN in the efficiency of holding is equal to or less than bigM value as shown in (24). Equation (25) indicates that the minimum investment level in LoRaWAN for improving the efficiency of holding is applied at the allocated warehouse at plant i. Equation (26) represents the constraint of the minimum level investment in LoRaWAN technology in holding operations. The minimum investment level in LoRaWAN technology to improve the efficiency of holding is equal to or greater than minimum level investment in LoRaWAN of A_h. See equation (26). Equation (27) represents the binary constraint. All decision variables in the model should be non-negative values for validation, as shown in Equation (28).

3.2.3 Mathematical Modeling of Scenario 3

Since the aim of the study is to reduce cost, the first term stands for the courier transportation delivery costs per item for all demanded products and each plant with no designated warehouse. The second term indicates the ordering cost of retailer and the cost of transportation for orders delivered from vendor to retailer under direct delivery policy. The third term stands for holding cost per item of the added average order quality and the safety stock level for all the products at each industrial plant with designated warehouses. The fourth term stands for the sum of total costs of the fixed cost of setting up the warehouses at each industrial plant as well as the rental cost for the assigned space by each plant for the vendor's warehousing purposes. The fifth and sixth terms stand for LoRaWAN holding and ordering investment costs for each plant with designated warehouses. See Equation
(29).

$$\textbf{Min} \sum_{i=1}^{n}\sum_{j=1}^{m}(TC_{ij} + OC_{ij})R_{ij}P_{dl} + \sum_{k=1}^{v}\sum_{l=1}^{r}\frac{D_k}{Q_k}(TC_l + OC_l) + \sum_{i=1}^{n}\sum_{j=1}^{m}HE_iHC_{ij}(\frac{Z_{ij}}{2} + L_{ij}) + \sum_{i=1}^{n}(SC_i + SS_iRe_i)P_{wi} + \sum_{i=1}^{n}L_{hi} + \sum_{i=1}^{n}L_{oi} \tag{29}$$

The constraints of scenario 3 are the constraints of scenario 1 and scenario 2, which are indicated by Equations

(7)-(20) and Equations (22)-(28).

4. Case Study: Pipe Manufacturing Integrated Supply Chain

A case study for pipe manufacturing integrated supply chain is used to demonstrate the efficiency of the model and the solutions obtained by firefly algorithm. This pipe manufacturing company produces three different types of pipes with different sizes: Glass Reinforced Plastic pipes (GRP), Glass Reinforced Epoxy pipes (GRE), and Reinforced Concrete pipes (RC), see Figure 4.

Figure 4. Types of pipes produced by the company

The main objective is to reduce the total cost of supply chain networks. The supply chain proposed for this case study is presented in Figure 5. The supply chain consists of a vendor warehouse with four suppliers, two manufacturing plants with assigned warehouses, and two manufacturing plants with no assigned warehouses. The manufacturing plants with assigned warehouses would share their existing capacities with the manufacturing plants with no assigned warehouses to reduce the costs associated with the inventory.

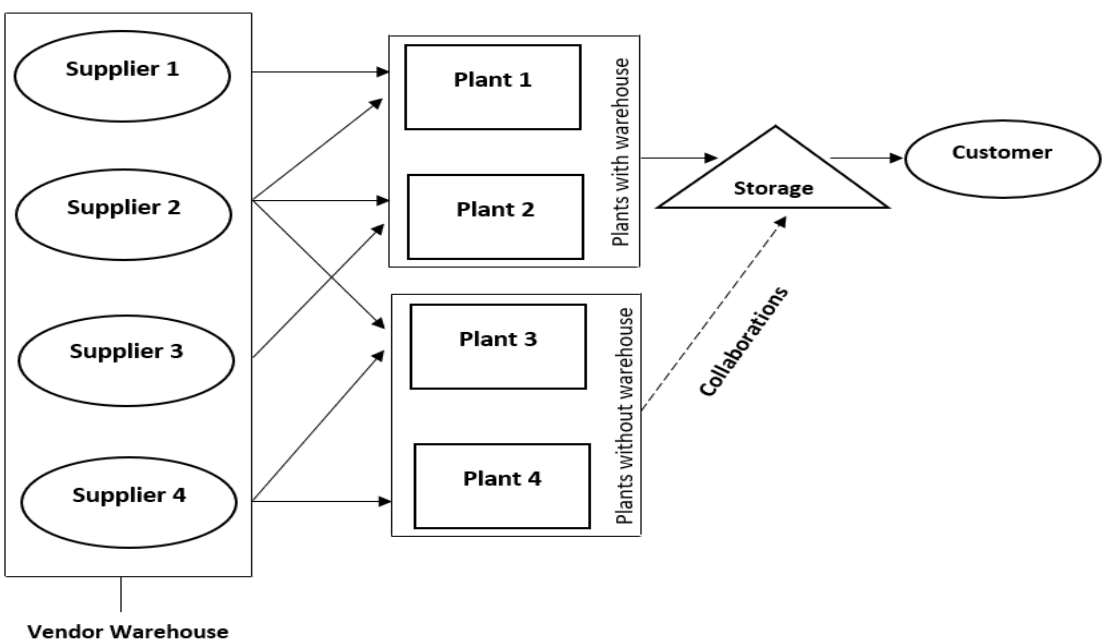

Figure 5. Supply chain for the case study

5. Results and Discussions

In this paper, we demonstrated the efficiency of the new modified firefly algorithm by comparing this modified FA with the standard firefly algorithm. We used two performance measures to exhibit the efficiency of the modified firefly algorithm. Table 2 represents the comparison between the standard firefly algorithm and the modified firefly algorithm that were used in this research. The proposed firefly algorithm looks through additional pursuit space. Thus, it could acquire progressively feasible solutions. In this paper, we set $\beta_0 = 1;\ \alpha = 0.5;\ and\ \Upsilon = 1$ as in (Sababha et al. 2018). We used MATLAB R2019a software to solve the problem. Table 2 represents the performance of the modified algorithm. In this paper, we considered the best solution as the cheaper cost based on running the minimization problem. It also represents the best solution found by the modified FA we applied. Moreover, the optimal solution is found. S1, S2, S3, M1, M2, M3, L1, L2, and L3, as shown in Table 2, represent small-sized problems for scenario 1, which is bounded by two plants and three items; small-sized problems for scenario 2, which is bounded by two plants and three items; small-sized problems for scenario 3, which is bounded by two plants and three items; medium-sized problems for scenario 1, which is bounded by three plants and three items; medium-sized problems for scenario 2, which is bounded by three plants and three items; medium-sized problems for scenario 3, which is bounded by three plants and three items; large-sized problems for scenario 1, which is bounded by eight plants and three items; large-sized problems for scenario 2, which is bounded by eight plants and three items; large-sized problems for scenario 3, which is bounded by eight plants and three items.

Table 2. The performance of the modified firefly algorithm

Problems	**Standard Firefly Algorithm**			**Modified Firefly Algorithm**			**Improvement (%) Based on Best Solutions**
	Iterations	Best Solutions	CPU Time	Iterations	Best Solutions	CPU Time	
SCENARIO3 – S3	35	3,151,172	37.23	25	2,001,259	34.85	36.49 %
SCENARIO2 – S2	48	4,275,397	39.61	31	3,109,224	36.46	27.27 %
SCENARIO1 – S1	53	5,634,126	45.20	45	4.445,375	41.09	21.10 %
SCENARIO3 – M3	77	7,433,533	51.62	43	6,526,987	46.91	12.20 %
SCENARIO2 – M2	94	8,748,017	167.31	59	7,153,188	145.48	18.23 %
SCENARIO1 – M1	105	9,675,020	389.43	67	8,394,010	309.78	13.24 %
SCENARIO3 – L3	112	10,721,571	672.74	75	9,710,824	565.23	9.43 %
SCENARIO2 – L2	153	11,248,113	927.43	94	10,232,390	750.76	9.03 %
SCENARIO1 – L1	221	13,953,899	1228.79	154	11,951,404	1122.66	14.35 %

As compared to the standard firefly algorithm, the modified FA performs more efficiently compared to the standard firefly algorithm with a significant reduction of best solution by 14.35% for large-sized problems of scenario 1, 9.03% for large-sized problems of scenario 2, and approximately 9.43% for large-sized problems of scenario 3. See Figure 6.

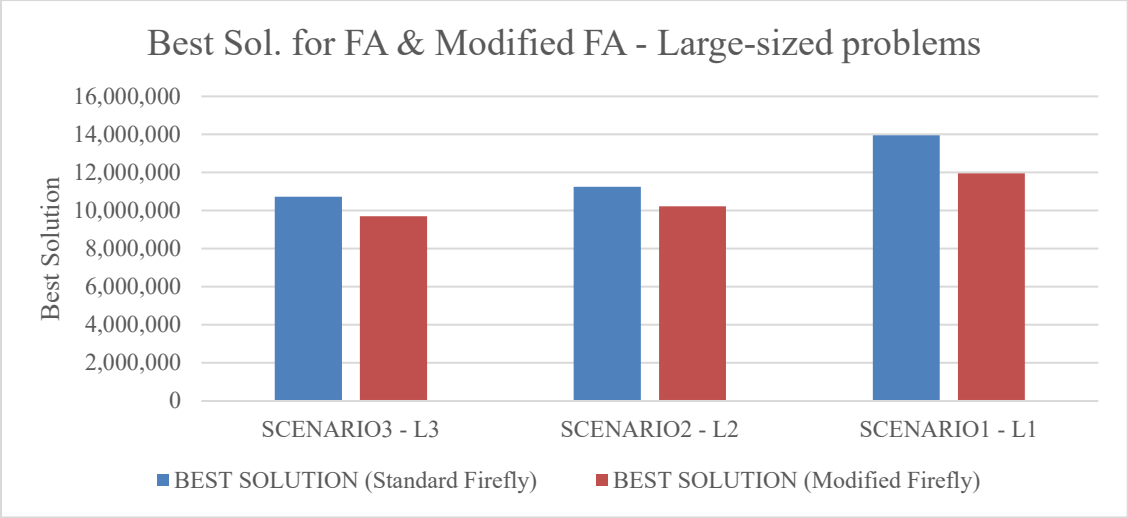

Figure 6. The best solution of standard FA & modified FA based on large-sized problems

In addition, the computational time was reduced based on the modified firefly algorithm performance by 8.64% for large-sized problems of scenario 1, 19.05% for large-sized problems of scenario 2, and approximately 15.98% for large-sized problems of scenario 3, as shown in Table 2. This indicates that the proposed algorithm is more efficient compared to the standard firefly algorithm. The computational time between the standard firefly algorithm and the modified firefly algorithm for different problem sizes is reduced, which indicates the better solution for modified FA, as shown in Figure 7.

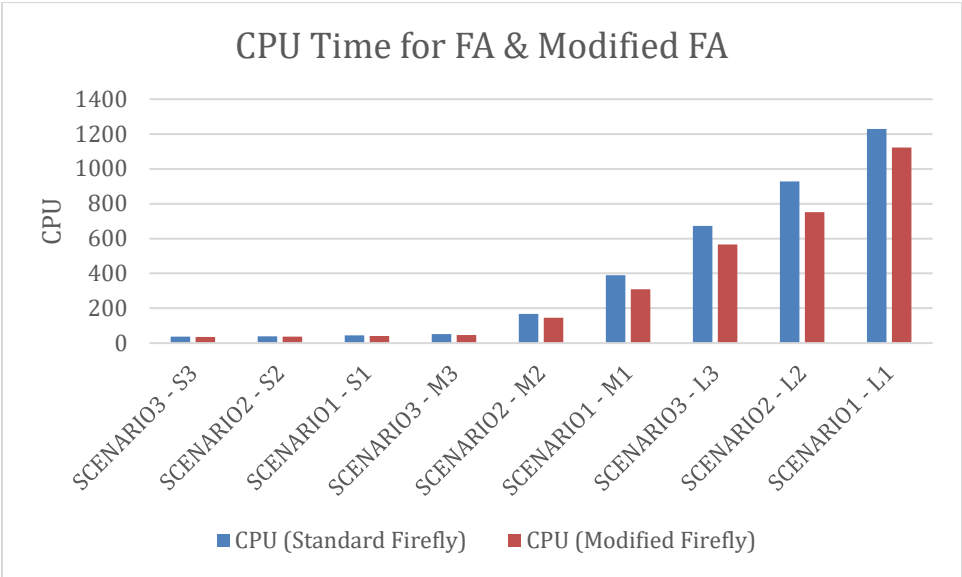

Figure 7. The computational time between the Modified FA and standard FA

We applied response surface methodology (RSM), which can approximate the behavior of the system, to tune the parameters of algorithms. The optimal values of parameters' algorithms are shown in Table 3. We also trained RSM, which is trained upon a design of experiment (DOE), based on four algorithms: statistical models (Kriging), advanced models (Radial Basis Functions), and classical model (stepwise regression & Polynomial singular value decomposition), see Table 4. Table 4 shows that the best value of the selected validation criterion is represented by the green row (Stepwise regression model) based on five performance indexes including mean absolute error, mean relative error, mean normalized error, R-Squared, and Akaike information criterion.

Table 3. The optimal values of parameters' algorithms

Problem		Standard FA				Modified FA				Run Time
		No. Population	β	ϒ	α	No. Population	β	ϒ	α	
Small	1	73.94	10.60	11.37	10.70	30.00	10.50	11.50	10.55	21.60
	2	72.93	10.60	10.60	10.69	30.00	10.50	10.50	10.52	23.60
	3	71.72	10.96	11.60	10.70	30.00	10.50	10.50	10.60	25.60
	4	80.00	10.60	11.60	10.70	29.10	10.50	10.50	10.51	26.60
	5	100.00	10.92	11.60	10.70	35.00	10.73	11.50	10.60	40.60
Large	1	123.44	11.60	11.60	10.77	40.86	11.60	11.60	10.68	121.10
	2	110.10	10.60	11.60	10.71	39.95	11.60	11.60	10.68	151.10
	3	130.10	11.60	10.60	10.80	39.74	11.60	10.60	10.64	172.60
	4	120.40	10.60	10.60	10.72	40.45	11.27	10.92	10.72	219.10
	5	150.60	10.60	10.60	10.67	44.95	11.60	10.60	10.66	283.10

Table 4. Model training using RSM algorithms

		Training Progress	RSM name	Mean Abs. Error	Mean Rel. Error	Mean Norm. Error	R-squared	AIC
1	☆	Finished	Kriging	2.8951E5	1.0330E-3	1.2872E-3	9.9998E-1	2.7517E2
2	☆	Finished	Polynomial SVD	1.1176E-7	3.3378E-16	4.9690E-16	1.0000E0	-2.2966E2
3	☆	Finished	Radia Basis Functions	1.8262E1	6.4664E-8	8.1195E-8	1.0000E0	1.2027E2
4	★	Finished	Stepwise Regression	8.1956E-8	2.6383E-16	3.6440E-16	1.0000E0	-2.3429E2

5. Conclusion

In this research, the problem was formulated as a mixed-integer non-linear programming (MINLP) model. For large problem sizes, the standard firefly algorithm was running; however, in the end we faced an issue that solutions do not enhance anymore. Thus, the proposed algorithm was applied to solve this issue based on the balance between exploitation and exploration. In this research, we developed the model for the deterministic approach considering the demand is deterministic. Further research can be extended to develop a model for a stochastic approach considering the demand is stochastic. The impact of the parameter setting of the modified algorithms could be determined by further studies.

References

Baysan, S., & Ustundag, A. The cost–benefit models for RFID investments. In *The value of RFID* (pp. 13-22). Springer, London, 2013.

Beliatis, M. J., Mansour, H., Nagy, S., Aagaard, A., & Presser, M. Digital waste management using LoRa network a business case from lab to fab. In *2018 Global Internet of Things Summit (GIoTS)* (pp. 1-6). IEEE, 2018.

Ben-Daya, M., Hassini, E., & Bahroun, Z. Internet of things and supply chain management: a literature review. *International Journal of Production Research*, *57*(15-16), 4719-4742, 2019.

Billington, P. J. The classic economic production quantity model with setup cost as a function of capital expenditure. *Decision sciences*, *18*(1), 25-42, 1987.

Fister Jr, I., Perc, M., Kamal, S. M., & Fister, I. A review of chaos-based firefly algorithms: perspectives and research challenges. *Applied Mathematics and Computation*, *252*, 155-165, 2015.

Gandomi, A. H., Yang, X. S., & Alavi, A. H. Mixed variable structural optimization using firefly algorithm. *Computers & Structures*, *89*(23-24), 2325-2336, 2011.

Govindan, K., Soleimani, H., & Kannan, D. Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European journal of operational research*, *240*(3), 603-626, 2015.

Gupta, A., Padhy, P. K. Modified Firefly Algorithm based controller design for integrating and unstable delay processes. *Engineering Science and Technology, an International Journal*, *19*(1), 548-558, 2016.

Huang, Y., Xu, Y., Qi, S., Fang, X., & Yin, X. Recent patents on RFID-based logistics management systems. *Recent Patents on Mechanical Engineering*, *9*(1), 26-36, 2016.

Karampatzakis, D., Avramidis, G., Kiratsa, P., Tseklidis, I., & Oikonomidis, C. A Smart Cargo Bike for the Physical Internet enabled by RFID and LoRaWAN. In *2019 Panhellenic Conference on Electronics & Telecommunications (PACET)* (pp. 1-4). IEEE, 2019.

Lee, I., & Lee, B. C. An investment evaluation of supply chain RFID technologies: A normative modeling approach. *International Journal of Production Economics*, *125*(2), 313-323, 2010.

Lee, Y. C., & Lee, S. S. The valuation of RFID investment using fuzzy real option. *Expert Systems with Applications*, *38*(10), 12195-12201, 2011.

Li, D., Li, J., & Zhang, Y. RFID investment evaluation model for EOQ inventory system with planned shortage. In *2016 35th Chinese Control Conference (CCC)* (pp. 8340-8345). IEEE, 2016.

Ogarkov, A. Usage of modern sensors and network technologies in context of supply chain management, 2019.

Sababha, M., Zohdy, M., and Kafafy, M., "The enhanced firefly algorithm based on modified exploitation and exploration mechanism." *Electronics* 7, no. 8, pp. 132, 2018.

Simon, D., *Evolutionary optimization algorithms*. John Wiley & Sons, 2013.

Talbi, E. G., *Metaheuristics: from design to implementation* (Vol. 74). John Wiley & Sons, 2009.

Wu, X., Yue, D., Bai, J., & Chu, C. H. A real options approach to strategic RFID investment decision. In *2009 IEEE international conference on RFID* (pp. 314-321). IEEE, 2009.

Yang, X. S. Firefly algorithm, stochastic test functions and design optimization. *arXiv preprint arXiv:1003.1409*, 2010.

Yang, X. S. Multiobjective firefly algorithm for continuous optimization. *Engineering with computers*, *29*(2), 175-184, 2013.

Yang, X. S., *Nature-inspired metaheuristic algorithms*. Luniver press, 2010.

Zhong, R. Y., Huang, G. Q., Lan, S., Dai, Q. Y., Chen, X., & Zhang, T. A big data approach for logistics trajectory discovery from RFID-enabled production data. *International Journal of Production Economics*, *165*, 260-272, 2015.

Biographies

Abdulhadi Altherwi is a lecturer in the Department of Industrial Engineering at Jazan University, Jazan, Saudi Arabia. He earned a B.S in Industrial Engineering from Jazan University, Jazan, Saudi Arabia and a Master's in industrial engineering from Lawrence Technological University, Michigan, USA. Altherwi is currently a full-time-Ph.D. student in Systems Engineering program at Oakland University, Michigan, USA. He has published conference papers in his field and is a member of IISE.

Mohamed Zohdy is a Professor of Electrical and Computer Engineering at Oakland University, Michigan, USA. He is founder of ICCC group. He earned a B.S. in Electrical Engineering from the University of Cairo, Egypt, and a master's and PhD in Electrical Engineering from the University of Waterloo, Canada. He has published journal and conference papers and has completed research projects with many local and global industries. He is an academic advisor for graduate students. His research interests include advanced control and estimation, intelligent pattern information processing, neural, fuzzy, evolutionary systems, chaos control, smart simulation, and hybrid systems. Dr. Zohdy has worked on research contracts with government, industry; he has also received recent seed funds on Fuel Cell modeling and control for transportation, which hold considerable promise for improving vehicle energy supply, FCA Powertrain controls, Lear Power Electronics, Kia Motors, NSF, and USAID.

Richard Olawoyin is an Associate Professor of Industrial and Systems Engineering (ISE) at Oakland University (OU), Rochester, Michigan teaching Engineering Risk Analysis, Statistical Methods in Engineering, Safety Engineering, Industrial and Systems Engineering, Human Factors Engineering and Occupational Biomechanics. He holds a BS in Geology (University of Calabar, Nigeria), MS and PhD in Energy Engineering (Penn. State University). His research interests emphasize on Industry X.0 Systems in areas of; statistics and artificial intelligence and big data risk analytics, digital supply chain networks, blockchain and stochastic trend modeling. He is a book author and has authored several book chapters and numerous peer-reviewed journal publications (more than 35 as first author). He is the assessment coordinator for the ISE department at Oakland University, he is an advisory council member for the ABET Inclusion and Diversity and Equity Advisory (IDEA) Council,

Daw Alwerfalli is a Professor and Director of Engineering Management Program, A. Leon Linton Department of Mechanical, Robotics and Industrial Engineering at Lawrence Technological University. Prominent professor, senior

technical industry consultant and manufacturing engineering educator with tremendous expertise in program and curriculum development in higher technical education. Dr. Alwerfalli is a Highly experienced and dedicated community leader with great ability to work with an array of constituencies and coalitions in developing shared organizational vision to create and implement strategies aimed at advancing common causes to accomplish goals in fulfilment of the organization's mission. He possesses good analytical and decision-making skills and the ability to conceptualize new initiatives and solutions to problems while possessing an outcomes orientation. He has presented many well recognized technical papers in local, national and international conferences.