Article

Designing a Renewable and Sustainable Phosphorus Fertilizer Supply Chain Network using an Ensemble Knowledge-based Heuristic-Metaheuristic Algorithm

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Abstract: Phosphorus (P) is the most important substance in inorganic fertilizers used in agriculture industry. In this study, a multi-product and multi-objective model is presented considering economic and environmental concerns to design a renewable and sustainable P-fertilizer supply chain management (PFSCM). To handle complexities of the proposed model, an ensemble knowledge-based three-stage heuristic-metaheuristic algorithm utilizing heuristic information available in the model, whale optimization algorithm, and variable neighborhood search (named H-WOA-VNS) is proposed. At first, a problem-dependent heuristic is designed to generate a set of near-optimal feasible solutions. These solutions are fed into a population-based whale optimization algorithm which benefits from both exploration and exploitation strategies. Finally, a single-solution metaheuristic based on variable neighborhood search is applied to further improve the quality of the solution using local search operators. The objective function of the algorithm is formulated as a weighted average function to minimize total economic cost, while increasing crop yield and P use efficiency. Experimental results over five synthetic datasets and a real case study of the P-fertilizer supply chain confirm the superiority of the proposed method against the state-of-the-art techniques. The results demonstrate that the proposed method performs well in optimizing both the economic cost and environmental issues.

Keywords: supply chain management; phosphorus fertilizers; environmental issues; sustainability; recycling policy; metaheuristic algorithm

1. Introduction

Phosphorus (P) is an indispensable nutrient, which is essential for the global food security and plays a vital role in the crop growth and soil productivity. Nevertheless, this essential substance has several environmental effects [1]. Based on the simulation results in 2020 by Nedelciu et al. [2], production of phosphate rock (PR) needs to double by 2050 compared to the present levels, in order to match the total P requirements. The limitation of P is often viewed as a "bottleneck" in agricultural industry [3].

Nowadays, investigating the supply chain management (SCM) is increasingly encouraged in mining, manufacturing, and agriculture. Optimizing SCM can be described as a strategic management considering other decisions in the whole supply chain. In today's economy, sustainability is one of the crucial issues. Hence, sustainable development has cached researchers' and industrial practitioners' minds to focus on SCM [4]. To design a renewable and sustainable Chemical P-fertilizer supply chain management (PFSCM), various challenges of the P-fertilizer manufacturing including mining of PR, P-loss among the supply chain, and environmental protection issues should be taken into account [5]. Mathematical modeling and optimizing the fertilizer supply chains, specifically PFSCM, is a neglected concern in the operational research aspect so far.

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Many techniques have been conducted to solve complex issues of the SCM problems. Traditional optimization techniques inherently suffer from high computation time complexity and local optimal stagnation. They mainly rely on the fitness function's derivatives to determine the direction of search to achieve the final solution. Moreover, they are very sensitive to the initial estimate which typically leads to converge into a local optima solution. As a result, these techniques cannot be effective enough to efficiently solve SCM problems. Over the past years, many metaheuristic algorithms have been introduced to solve real-world SCM optimization problems. However, their performance is not guaranteed for the various problems as they are random search techniques. Therefore, there is a need to utilize practical algorithms utilizing the heuristic information available in the problem model [6]. Accordingly, hybrid heuristic-metaheuristic techniques are recently more favored for solving complex optimization problems [7-10].

Contrary to the previous studies, this paper aims to address a combined three-stage heuristic-metaheuristic approach with global and local search strategies to find a high speed, high precision, and high solution quality in solving the sustainable PFSCM. In this regard, a problem-dependent heuristic is proposed to generate a set of feasible solutions as the initial population of the population-based metaheuristic phase, i.e., a whale optimization algorithm (WOA), and then, followed by the single-solution metaheuristic phase, i.e., variable neighborhood search (VNS). The key contributions outlined in this paper can be summarized as follows:

- Designing a renewable and sustainable closed-loop supply chain network for the chemical P-fertilizers industry.
- Utilizing P recycling policy to reduce economic costs and improve sustainability.
- Proposing an ensemble three-stage heuristic-metaheuristic algorithm (named H-WOA-VNS) utilizing heuristic information and global/local search metaheuristics based on WOA and VNS with multiple local search operators, for the first time in solving supply chain management problems.
- Developing a backward knowledge-based heuristic from demand nodes to suppliers to provide the metaheuristic algorithms with a set of near-optimal feasible solutions as the start point for further searching.
- Applying VNS utilizing multiple local search operators on the global best solution found by the WOA;
- Alleviating effects of the PFSCM on the environment by promoting P use efficiency and crop yield improvement.

The rest of this paper is structured as follows: Section 2 studies the literature in two aspects, including fertilizers supply chain and solution methods. Section 3 is dedicated to sustainable PFSCM modeling. Section 4 presents the proposed H-WOA-VNS algorithm. Eventually, Section 5 provides the case study and discusses the results. Finally, Section 6 concludes this paper with future perspectives.

2. Literature Review

Over the recent years, along with the increasing development in various industries, conducting academic research on optimizing and finding practical solutions to solve the SCM problems prospered more. According to existing literature, the scope of this paper is related to two main flows of the SCM: research related to the P-fertilizer supply chains and studies devoted to the solution methods, which are described in the following.

2.1. P-fertilizer Supply Chain

The chemical P-fertilizer industry is associated with mining and processing of raw materials such as sulfur ores, phosphate ores, potassium salts, etc., manufacturing fertilizers, and distributing them [11]. Among essential nutrients, P is the pillar of the food security. Despite this fact, PR is a finite and non-renewable mineral resource [12]. Because of the highly dissipative nature of P, improving P use efficiency (PUE) is essential to minimize its effects on the aquatic systems and biodiversity [13].

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Chemical P-fertilizers include low, medium, and high PR processing. The most widely used low-medium PR processing P-fertilizers are single super phosphate (SSP) and triple super phosphate (TSP), while high PR processing P-fertilizers include mono ammonium phosphate (MAP), di-ammonium phosphate (DAP), etc. [14]. Overdoing such P-fertilizers harms the environment and ecosystem by emitting greenhouse gasses (GHG) to atmosphere, which cannot be neglected in agricultural industry [15].

Optimizing the P flow from suppliers (PR mines) to consumers (farms) has been considered as the most practical approach to improving the PUE. Though, appropriate strategies are lacking for the maximizing PUE by linking soil-crop system and fertilizer types with the P flow, from a whole PFSCM perspective. The currently available PR reserves are available in a few countries. The abundance of currently known PR reserves can avoid supply bottlenecks in the short and midterms. Over the past years, various policies have been employed to enhance the PUE in agriculture industry [16]. The maintenance and build-up method has been employed to manage soils with high P accumulation sustainable P. Moreover, feeding roots rather than the soil was used to exploit soil legacy P for achieving a higher PUE and crop yield [17]. Recently, concerns about agricultural sustainability have focused on developing techniques that are effective and available for farmers, while do not have adverse impacts on the environment [18].

The impact of P-fertilizers on PUE was analyzed from a supply chain point of view in different researches [19, 20]. To secure and maintain food sustainability, it is essential to ensure the continued supply of PR and find new strategic options that can respond to the P supply chain problems. To help the communities in this regard, researches on the interaction and making trade-offs among the different levels of the supply chain are warranted for the decision makers. However, improving the P flow among different echelons of the P supply chain and P-fertilizer distribution that can develop a sustainable PFSCM is still an unclear area in literature. Promoting PFSCM efficiencies (especially in environmental effects and crop yield), such as mining, production, distribution, inventory flow, etc., are the hot subjects of the research. To the best of our knowledge, a comprehensive study on optimizing closed-loop renewable P supply chain network considering economic and environmental aspects is yet not to be reported elsewhere.

2.2. Solution Methods

There are different solution techniques for the optimization of supply chain management problems. Generally, the existing solution search methods can be classified into exact, heuristic, and random (metaheuristic) algorithms. Exact (complete or exhaustive search) methods guarantee to obtain an optimal solution for finite-size combinatorial optimization problems within a finite running time or prove that no feasible solution exists toward a reasonable run-time [21]. The main disadvantage of exact methods is their computational time that exponentially grows with the problem size. In this regard, it cannot be applied to solve real-size problems such as the sustainable SCM problems [22]. Moreover, a high-performance exact algorithm for a specific problem is often challenging to be extended to another problem when its formulation would be changed [23,24]. In these cases, the optimal solution is sacrificed by finding near-optimal solutions using heuristics or metaheuristics in a reasonable time [25].

Majority of real-world SCM problems are complex and large in size, so they cannot be optimally solved by exact search methods within an acceptable and reasonable time. Heuristics are an alternative way to find acceptable solutions with a reasonable time. They may also offer an optimal solution in some cases [26]. However, one of their weaknesses is falling into local optimal traps and not crossing them. Therefore, metaheuristic algorithms have been proposed to deal with such lacks, where the application of these methods in complicated problems is growing extensively.

Over the past years, a great deal of effort has been invested in the field of developing metaheuristics to solve medium- and large-size SCM optimization problems. They yield a computationally efficient and convergent procedure for such problems [27]. These

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methods can be categorized into evolutionary, swarm intelligence, physics-based, and human behavior-based algorithms. The main advantage of such methods is their utilization of the 'trial-and-error' principle in their search process for an optimal solution. In recent years, metaheuristics have been successfully performed to solved complex problems like various SCM problems [28-32].

2.3. Our Contribution Against Existing Methods

The literature proves that hybridizing metaheuristics with other soft computing techniques is a suitable way to benefit from the advantages of the basic algorithms [33-36]. Generally, metaheuristics outperform heuristics in term of converging to a solution with higher quality. However, they require more computational resources and running time than the heuristics. As an appealing solution by exploiting problem-dependent heuristic information available in the problem model, heuristic-empowered metaheuristics can achieve a better trade-off between complexity and efficiency by utilizing heuristic information in different phases of metaheuristic (e.g., initial population generation and population updating) [6]. Accordingly, this study focuses on optimizing a sustainable PFSCM by applying a hybrid three-stage algorithm based on heuristic information and two popular metaheuristics (population-based WOA and solution-based VNS) to obtain a high-quality solution while reducing running time. In this regard, a problem-dependent heuristic is performed to generate a set of near-optimal feasible initial solutions for the first metaheuristic phase (i.e., the WOA phase), and then, the second metaheuristic phase (i.e., the VNS phase) is applied to further enhance the global best solution found by WOA through multiple local search operators.

3. Sustainable PFSCM Model

3.1. Supply Chain Network

This paper designs a six-echelon closed-loop PFSCM model comprising P-mines ($i \in I$), suppliers of raw materials ($j \in J$), fertilizer manufacturers ($m \in M$), distribution centers ($d \in D$), farms ($f \in F$), and the recycling center, as shown in Fig. 1. The model is formulated in T time periods ($t \in T$), i.e., months. Raw materials ($r \in R$) include sulfuric acid (SA), phosphoric acid (PA), and ammonium (A), where PA is made from P and SA. Moreover, four types of products ($p \in P$) including low-medium-grade P-fertilizers (SSP and TSP) and high-grade P-fertilizers (MAP and DAP), are considered. At every month t, each P-mine i or each supplier j may supply raw materials to one or more manufacturers up to its maximum capacity. Each manufacturer m may be sourced by one, two, or more P-mines and suppliers. Each distributor d can purchase the required fertilizers from various manufacturers until satisfying its total demand. Then, each distributor delivers the received SSP, TSP, MAP, and DAP fertilizers to the corresponding farms (i.e., demand nodes). Every farm f has a demand DP_{ft} of the total P-uptake by different fertilizers. Moreover, the P-uptake from each fertilizer p should be within $[LP_{fpt}, UP_{fpt}]$. At the end of every time period t, P-leaching from the different farms is collected and transferred to the recycling center to recycle them and provide phosphate, which can be used as a P supplier in the next time period t+1.

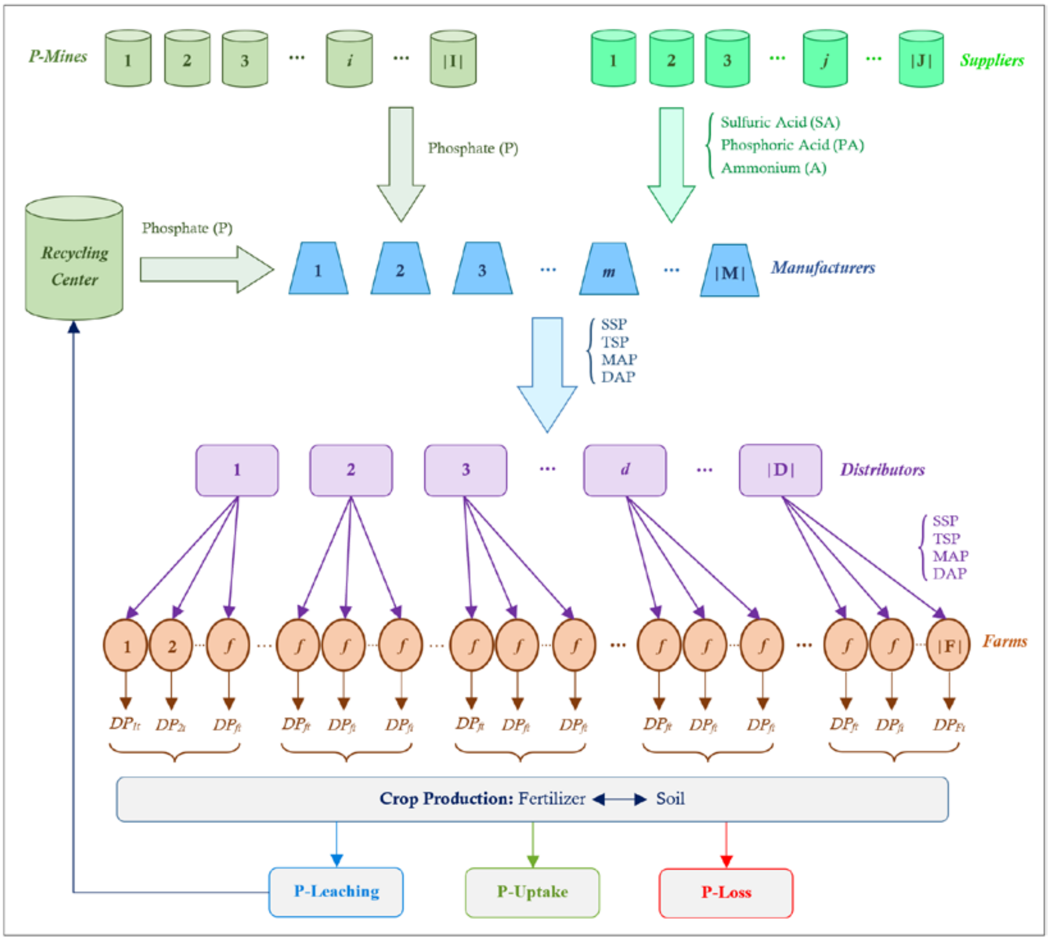

Figure 1. The PFSCM model.

The proposed PFSCM model is supposed to the following conditions:

- P is the main resource of producing P-fertilizers.
- There are three raw materials: SA, PA, and A.
- There are four P-fertilizer products: SSP, TSP, MAP, and DAP.
- To produce a unit of SSP, $U_1^P = 0.64$ unit of P and $U_{31}^S = 0.37$ unit of SA are used.
- In the production of a unit of TSP, $U_2^P = 0.4$ unit of P and $U_{22}^S = 0.34$ unit of PA are consumed.
- To produce a unit of MAP, $U_{13}^S = 0.12$ unit of A and $U_{23}^S = 0.51$ unit of PA are used.
- In the production of a unit of DAP, $U_{14}^S = 0.23$ unit of A and $U_{24}^S = 0.47$ unit of PA are consumed.
- PA is considered as a raw material ignoring the production procedure.
- Each manufacturer has a limited capacity to store P-fertilizers.
- Distribution centers can store a part of the received P-fertilizers.
- Lead time of P-recycling is assumed to be one month: the collected P-leaching from farms in each month would be recycled and can be considered as a P supplier in the next month.
- Each mine has a limited capacity to provide P at each month.
- Each supplier has a specific capacity to provide raw material at each month.
- Each manufacturer may produce one, two, three, or four P-fertilizer types, each with a limited capacity.
- The demand of each farm in terms of the total P-uptake and minimum/maximum required level of each type of fertilizer is assumed to be known for every month.

3.2. Notations

The notations of the PFSCM model are provided in Table 1. To solve the model via H-WOA-VNS and empower it to satisfy the constraints, we distinguish two types of decision variables (DVs): direct DVs and indirect DVs. The direct DVs are those which are encoded into feasible solutions and optimized using H-WOA-VNS, while the indirect DVs are decoded based on the model parameters and the direct DVs.

Table 1. List of indices, sets, parameters, and decision variables.

Sets and Indices	Definition
$i \in I$	Set of P-mines (suppliers of phosphorus)
$j \in J$	Set of suppliers of raw materials
$m \in M$	Set of manufacturers
$d \in D$	Set of distributors
$f \in F$	Set of farms (demand nodes)
$t \in T$	Set of months (time periods)
$r \in R$	Set of raw materials: A (r=1), PA (r=2), and SA (r=3)
$p \in P$	Set of products: SSP (p=1), TSP (p=2), MAP (p=3), and DAP (p=4)
Parameters	**Definition**
B_{fd}	1 if farm f is supported by distribution center d; 0 otherwise
BS_p	Batch size of ordering fertilizer p by farms (ton)
Cap_{it}^{P}	Capacity of supplying P by mine i in time t (ton)
Cap_{jrt}^{S}	Capacity of supplier j to supply raw material r in time t (ton)
Cap_{mp}^{M}	Capacity of manufacturer m to produce fertilizer p in each time (ton)
W_m^M	Warehouse capacity of manufacturer m (ton)
W_d^D	Warehouse capacity of distribution center d (ton)
W^R	Warehouse capacity of recycling center (ton)
U_p^P	Required P rock to produce unit fertilizer p (%)
U_{rp}^S	Required raw material r for the production of unit fertilizer p (%)
α_{fp}	Phosphorus uptake by farm f from unit fertilizer p (%)
β_{fp}	Crop yield increasement in farm f from unit fertilizer p (%)
γ_{fp}	Recyclable phosphorus in farm f from unit fertilizer p (%)
λ_p	Total phosphorus loss to produce a unit of fertilizer p (%)
μ_p	Amount of recyclable P per unit P-leaching of fertilizer p (%)
DP_{ft}	Phosphorus demand by farm f in time period t (ton)
LP_{fpt}	Minimum amount of fertilizer p which should be delivered to farm f in time t (ton)
UP_{fpt}	Maximum amount of fertilizer p which should be delivered to farm f in time t (ton)
TC_{im}^{PM}	Transportation cost of carrying phosphorus from mine i to manufacturer m ($/ton)
TC_m^{RM}	Transportation cost of carrying phosphorus from recycling center to manufacturer m ($/ton)
TC_{jm}^{SM}	Transportation cost from supplier j to manufacturer m for carrying raw materials ($/ton)
TC_{md}^{MD}	Transportation cost of carrying fertilizers from manufacturer m to distribution center d ($/ton)
TC_{df}^{DF}	Transportation cost of carrying fertilizers from distribution center d to farm f ($/ton)
TC_f^{FR}	Transportation cost of carrying phosphorus leaching from farm f to recycling center ($/ton)
BC_i^P	Purchasing cost of phosphate from mine i ($/ton)
BC_{jr}^S	Purchasing cost from supplier j for raw material r ($/ton)
PC_{mp}	Production cost in manufacturer m for unit fertilizer p ($/ton)
RC	Recycling cost of unit P in recycling center ($/ton)
I_{mp}^0	Initial inventory of fertilizer p in manufacturer m (ton)
IC_m^M	Inventory cost in manufacturer m for each month ($/ton/month)
IC_d^D	Inventory cost in distribution center d for each month ($/ton/month)
IC^R	Inventory cost in recycling center for each month ($/ton/month)

Direct DVs	Definition
P_{mpt}	Amount of fertilizer *p* produced in time *t* by manufacturer *j* (ton)
R_{fpt}	Amount of fertilizer *p* delivered in time *t* to farm *f* (BSp)
PLM	Priority list of manufacturers determining their order in P-mine and supplier assignment
SLP_m	Selection list of P-mines (plus recycling center) for manufacturer *m*
SLS_m	Selection list of suppliers for manufacturer *m*
PLD	Priority list of distributors determining the order of distributors in manufacturer assignment
SLM_d	Selection list of manufacturers for distributor *d*
Indirect DVs	**Definition**
SP_{mrpt}	Required amount of raw material *r* in manufacturer *m* to produce fertilizer *p* in time *t* (ton)
S_{mrt}	Required raw material *r* in manufacturer *m* to produce all fertilizers in time *t* (ton)
RP_t	Total P recycled at time *t* (ton)
TD_{dpt}	Total demand of fertilizer *p* in distribution center *d* in time *t* (ton)
X_{imt}^P	1 if mine *i* supplies P for manufacturer *m* in time *t*; 0 otherwise
X_{mt}^R	1 if the recycling center supplies P to manufacturer m in time t; 0 otherwise
X_{jmrt}^S	1 if supplier *j* supplies raw material *r* to manufacturer *m* in time *t*; 0 otherwise
X_{mdpt}^M	1 if fertilizer *p* is delivered from manufacturer *m* to distribution center *d* in time *t*; 0 otherwise
X_{dfpt}^D	1 if fertilizer *p* is delivered from distribution center *d* to farm *f* in time *t*; 0 otherwise
X_{fpt}^F	1 if P-leaching of fertilizer *p* is delivered from farm *f* to the recycling center in time *t*; 0 otherwise
Y_{imt}^P	Amount of P delivered in time *t* from mine *i* to manufacturer *m* (ton)
Y_{mt}^R	Amount of P transferred in time *t* from the recycling center to manufacturer *m* (ton)
Y_{jmrt}^S	Amount of raw material *r* transferred in time *t* from supplier *j* to manufacturer *m* (ton)
Y_{mdpt}^M	Amount of fertilizer *p* transferred in time *t* from manufacturer *m* to distribution center *d* (ton)
Y_{dfpt}^D	Amount of fertilizer *p* transferred in time *t* from distribution center *d* to farm *f* (ton)
Y_{fpt}^F	Amount of P-leaching of fertilizer *p* transferred in time *t* from farm *f* to the recycling center (ton)
IP_{mpt}	Inventory of manufacturer *m* for fertilizer *p* at time *t* (ton)
ID_{dpt}	Inventory of distribution center *d* for fertilizer *p* at time *t* (ton)
IR_t	Inventory of recycled P in the recycling center at time *t* (ton)

3.3. Problem Formulation

In this section, the proposed PFSCM model is formulated as a multi-objective problem to minimize the total economic cost, while maximizing the crop yield and PUE. By using mixed integer linear programming (MILP), a mathematical model of the PFSCM is provided in the following.

3.3.1. Economic Objective Function

Total economic cost comprises the purchasing cost of P from P-mines (C_{PP}), the purchasing cost of raw materials from suppliers (C_{PS}), the production cost of the manufacturers (C_{PR}), the recycling cost in the recycling center (C_{RC}), transportation cost (C_{TR}), and inventory holding cost (C_{IH}), which are addressed in Eqs. (1)-(6), respectively.

$$C_{PP} = \sum_i (BC_i^P \sum_t \sum_m Y_{imt}^P X_{imt}^P) \tag{1}$$

$$C_{PS} = \sum_j \sum_r (BC_{jr}^S \sum_t \sum_m Y_{jmrt}^S X_{jmrt}^S) \tag{2}$$

$$C_{PR} = \sum_m \sum_p PC_{mp} \sum_t P_{mpt} \tag{3}$$

$$C_{RC} = \sum_{t} \left(RC \sum_{f} \sum_{p} \mu_p Y^F_{fpt} X^F_{fpt} \right) \tag{4}$$

$$\begin{aligned} C_{TR} = {} & \sum_{t} \sum_{i} \sum_{m} TC^{PM}_{im} Y^P_{imt} X^P_{imt} + \sum_{t} \sum_{m} TC^{RM}_{m} Y^R_{mt} X^R_{mt} + \sum_{t} \sum_{j} \sum_{m} \sum_{r} TC^{SM}_{jm} Y^S_{jmrt} X^S_{jmrt} \\ & + \sum_{t} \sum_{m} \sum_{d} \sum_{p} TC^{MD}_{md} Y^M_{mdpt} X^M_{mdpt} + \sum_{t} \sum_{d} \sum_{f} \sum_{p} TC^{DF}_{df} Y^D_{dfpt} X^D_{dfpt} \\ & + \sum_{t} \sum_{f} \sum_{p} TC^{FR}_{f} Y^F_{fpt} X^F_{fpt} \end{aligned} \tag{5}$$

$$C_{IH} = \sum_{t} \sum_{m} \sum_{p} \left(IC^M_m IP_{mpt} \right) + \sum_{t} \sum_{d} \sum_{p} \left(IC^D_d ID_{dpt} \right) + \sum_{t} \left(IR^R \, IR_t \right) \tag{6}$$

By aggregation of the six economic costs, the economic objective function can be expressed as:

$$\begin{aligned} \text{minimize } Z_{EC} = {} & C_{PP} + C_{PS} + C_{PR} + C_{RC} + C_{TR} + C_{IH} \\ = {} & \left(\sum_{i} \left(BC^P_i \sum_{t} \sum_{m} Y^P_{imt} X^P_{imt} \right) \right) + \left(\sum_{j} \sum_{r} \left(BC^S_{jr} \sum_{t} \sum_{m} Y^S_{jmrt} X^S_{jmrt} \right) \right) \\ & + \left(\sum_{m} \sum_{p} PC_{mp} \sum_{t} P_{mpt} \right) + \left(\sum_{t} \left(RC \sum_{f} \sum_{p} \mu_p Y^F_{fpt} X^F_{fpt} \right) \right) \\ & + \Bigg(\sum_{t} \sum_{i} \sum_{m} TC^{PM}_{im} Y^P_{imt} X^P_{imt} + \sum_{t} \sum_{m} TC^{RM}_{m} Y^R_{mt} X^R_{mt} \\ & + \sum_{t} \sum_{j} \sum_{m} \sum_{r} TC^{SM}_{jm} Y^S_{jmrt} X^S_{jmrt} + \sum_{t} \sum_{m} \sum_{d} \sum_{p} TC^{MD}_{md} Y^M_{mdpt} X^M_{mdpt} \\ & + \sum_{t} \sum_{d} \sum_{f} \sum_{p} TC^{DF}_{df} Y^D_{dfpt} X^D_{dfpt} + \sum_{t} \sum_{f} \sum_{p} TC^{FR}_{f} Y^F_{fpt} X^F_{fpt} \Bigg) \\ & + \left(\sum_{t} \sum_{m} \sum_{p} \left(IC^M_m IP_{mpt} \right) + \sum_{t} \sum_{d} \sum_{p} \left(IC^D_d ID_{dpt} \right) + \sum_{t} \left(IR^R \, IR_t \right) \right) \end{aligned} \tag{7}$$

3.3.2. Environmental Objective Functions

In the proposed model, two environmental objectives are used to increase the crop yield (Z_{CY}) and PUE (Z_{PUE}), which are formulated in Eqs. (8) and (9), respectively. As P is a non-sustainable resource, it is of utmost importance to reduce the total P-loss which is described as the total losses from the exploited PR to that of uptake by the plants.

$$\text{maximize } Z_{CY} = \sum_{f} \sum_{p} \beta_{fp} \left(\sum_{t} \sum_{d} Y^D_{dfpt} X^D_{dfpt} \right) \tag{8}$$

$$\text{maximize } Z_{PUE} = \sum_{p} (1 - \lambda_p) \left(\sum_{f} \left[\alpha_{fp} \sum_{d} \sum_{t} Y^D_{dfpt} X^D_{dfpt} + \gamma_{fp} \sum_{d} \sum_{t} Y^D_{dfpt} X^D_{dfpt} \right] \right) \tag{9}$$

3.3.3. Multi-Objective Function

To solve the multi-objective problem, the objective functions Z_{EC}, Z_{CY}, and Z_{PUE}, are aggregated into a single-objective formula by means of a weighted averaging method. The economic objective Z_{EC} is calculated in $ to be minimized, while the environmental objectives are to be maximized. To be able of combining the different objective functions, all objective functions are normalized into $\overline{Z_{EC}}$, $\overline{Z_{CY}}$, and $\overline{Z_{PUE}}$, to be minimized within [0,1] considering the minimum and maximum expected values for each objective function. As a result, the total objective function can be expressed as:

$$\text{minimize } OF = [w_{EC}\overline{Z_{EC}} + w_{CY}(1-\overline{Z_{CY}}) + w_{PUE}(1-\overline{Z_{PUE}})] \times PF \tag{10}$$

where w_{EC}, w_{CY}, and w_{PUE} ($w_{EC}+w_{CY}+w_{PUE}=1$), are constant parameters which determine the relative impact of Z_{EC}, Z_{CY}, and Z_{PUE}, within the objective function. Moreover, PF is a penalty function calculated as $PF=2^{NumP}$, where $NumP$ is the number of constraints in Eqs. (11)-(34) which have not been satisfied.

Subject to:

$$\sum_p \left(a_{fp} \sum_d Y^D_{dfpt} X^D_{dfpt} B_{fd} \right) \geq DP_{ft} \qquad \forall f, \forall t \tag{11}$$

$$LP_{fpt} \leq \sum_d Y^D_{dfpt} X^D_{dfpt} B_{fd} \leq UP_{fpt} \qquad \forall f, \forall p, \forall t \tag{12}$$

$$\sum_d Y^D_{dfpt} X^D_{dfpt} B_{fd} = R_{fpt} BS_p \qquad \forall f, \forall p, \forall t \tag{13}$$

$$X^D_{dfpt} \leq B_{fd} \qquad \forall d, \forall f, \forall p, \forall t \tag{14}$$

$$\sum_d X^D_{dfpt} = 1 \qquad \forall f, \forall p, \forall t \tag{15}$$

$$ID_{dp0} = 0 \qquad \forall d, \forall p \tag{16}$$

$$ID_{dpt-1} + \sum_m Y^M_{mdpt} X^M_{mdpt} \geq \sum_f Y^D_{dfpt} X^D_{dfpt} B_{fd} \qquad \forall d, \forall p, \forall t \tag{17}$$

$$ID_{dpt} = ID_{dpt-1} + \sum_m Y^M_{mdpt} X^M_{mdpt} - \sum_f Y^D_{dfpt} X^D_{dfpt} B_{fd} \qquad \forall d, \forall p, \forall t \tag{18}$$

$$\sum_p ID_{dpt} \leq W^D_d \qquad \forall d, \forall t \tag{19}$$

$$P_{mpt} \leq Cap^M_{mp} \qquad \forall m, \forall p, \forall t \tag{20}$$

$$\sum_i Y^P_{imt} X^P_{imt} + Y^R_{mt} X^R_{mt} \geq \sum_p U^P_p P_{mpt} \qquad \forall m, \forall t \tag{21}$$

$$\sum_j Y^S_{jmrt} X^S_{jmrt} \geq \sum_p U^S_{rp} P_{mpt} \qquad \forall m, \forall r, \forall t \tag{22}$$

$$IP_{mp0} = I^0_{mp} \qquad \forall m, \forall p \tag{23}$$

$$IP_{mpt-1} + P_{mpt} \geq \sum_d Y^M_{mdpt} X^M_{mdpt} \qquad \forall m, \forall p, \forall t \tag{24}$$

$$IP_{mpt} = IP_{mpt-1} + P_{mpt} - \sum_d Y^M_{mdpt} X^M_{mdpt} \qquad \forall m, \forall p, \forall t \tag{25}$$

$$\sum_{p} IP_{mpt} \le W_m^M \qquad \forall m, \forall t \tag{26}$$

$$\sum_{m} Y_{jmrt}^S X_{jmrt}^S \le Cap_{jrt}^S \qquad \forall j, \forall r, \forall t \tag{27}$$

$$\sum_{m} Y_{imt}^P X_{imt}^P \le Cap_{it}^P \qquad \forall i, \forall t \tag{28}$$

$$\sum_{f}\sum_{p} Y_{fpt}^F X_{fpt}^F \le \sum_{d}\sum_{f}\sum_{p} \frac{\gamma_{fp}}{\mu_p} Y_{dfpz}^D X_{dfpz}^D B_{fd} \qquad \forall t \tag{29}$$

$$\sum_{m} Y_{mt}^R X_{mt}^R \le \sum_{z=1}^{t-1}\sum_{f}\sum_{p} \mu_p Y_{fpt}^F X_{fpt}^F - \sum_{z=1}^{t-1}\sum_{m} Y_{mz}^R X_{mz}^R \qquad \forall t \tag{30}$$

$$IR_0 = 0 \tag{31}$$

$$\sum_{m} Y_{mt}^R X_{mt}^R \le IR_{t-1} \qquad \forall t \tag{32}$$

$$IR_t = IR_{t-1} - \sum_{m} Y_{mt}^R X_{mt}^R + \sum_{f}\sum_{p} \mu_p Y_{fpt}^F X_{fpt}^F \qquad \forall t \tag{33}$$

$$IR_t \le W^R \qquad \forall t \tag{34}$$

Constraints (11) and (12) are related to farms. Constraint (11) indicates the total P-uptake demand of farm f at each time period t. In other words, the monthly demand of each farm must be met by the P-uptake from all types of P-fertilizers received from different distribution centers. Constraint (12) expresses the boundaries of the required amount of different fertilizer types by each demand node. In fact, the amount of fertilizers purchased from all distributors to farm f should be between the minimum and maximum amounts of demand for each fertilizer p.

Constraints (13-19) describe the constraints of the distribution centers. Constraint (13) shows that the amount of fertilizer p delivered to farm f at time t is equal to the summation of the delivered fertilizer p from different distributors. Constraint (14) indicates whether farm f is supported by distributor d to purchase fertilizer p or not. Constraint (15) ensures that farm f is sourced for fertilizer p by one distributor at each period t. Constraint (16) expresses that the initial inventory of distributor d for fertilizer p is zero. Constraints (17) illustrate that the total inventory and purchased product items of fertilizer p through all manufacturers by distribution center d at time t must be at least equal to under-support farms' demands. Constraint (18) calculates the total inventory of fertilizer p in distribution center d at the end of time t. Constraint (19) ensures that the total inventory of all types of fertilizers held by distributor d at time t do not exceed its warehouse capacity.

Constraints (20-26) are related to the manufacturers. Constraint (20) indicates that the produced fertilizer p by manufacturer j at time t must not exceed a certain capacity. Constraint (21) indicates that the total amounts of carried PR from the mines and carried P from recycling center to manufacturer m at time t must at least fulfill that manufacturer P requirement to satisfy all of its demands. Constraint (22) addresses that total raw material r transferred from all suppliers to manufacturer m at time t must at least fulfill the required raw materials for the production of all fertilizers. Constraint (23) describes the initial inventories of the manufacturers for each P-fertilizer. Constraint (24) ensures that the total inventory of fertilizer p in manufacturer m at time t satisfies the requirements of its under-support distribution centers. Constraint (25) updates the total inventory of manufacturer

m for fertilizer p at the end of time t. Constraint (26) indicates that the total inventory of all fertilizers at time t do not exceed the warehouse capacity of manufacturer m.

Constraints (27) and (28) address the supplying capacity of the P and raw materials. Constraint (27) expresses that the amount of raw material r carried from supplier j to manufacturer m at time t does not exceed the production capacity of supplier j. Constraint (28) indicates that the amount of carried P from the P-mine i to manufacturer m at time t does not exceed the capacity of P-mine i.

Constraints (29-34) are related to the recycling center. Constraint (29) calculates the total collected P obtained by P leach of all utilized fertilizers in all farms to the recycling center at period t. Constraint (30) expresses the total amount of manufacturers' requirements sourced through utilizing recycled P by the recycling center at period t. Constraint (31) denotes that the initial inventory of the recycling center is zero. Constraint (32) limits the inventory of recycled P at the recycling center at the end of every time period. Constraint (33) expresses the updated inventory of the recycling center at time t. Constraint (34) ensures the inventory held at the recycling center at time t must not be higher than its warehouse capacity.

4. Solution Method Using H-WOA-VNS

Generally, SCM is an NP-hard combinatorial optimization problem [37-39], and consequently, implementing exact methods with an exhaustive search strategy cannot be applicable due to the required computational resources for real-size SCMs. In this case, heuristic and/or metaheuristic algorithms can be adopted. Heuristics are problem-dependent techniques which are specifically designed for solving a problem utilizing the available information in the problem model [40]. These algorithms are rapid and easy to use, however, they do not effectively investigate the whole search space. In contrast, metaheuristics are higher-level iterative-based random search techniques which can obtain a better solution quality, by accepting more running time [41].

Based on the number of solutions encountered in each iteration, metaheuristics can be categorized into population-based (global search) and solution-based (local search) approaches [42]. Population-based metaheuristics investigate the search space in parallel (i.e., more exploration), while solution-based metaheuristics attempt to locally improve the quality of the current solution using local search operators (i.e., more exploitation). To achieve a better trade-off between solution quality and speed, we propose a combined three-stages heuristic-metaheuristic approach with balanced exploration-exploitation strategies, to efficiently solve the PFSCM model. In the first stage, a heuristic algorithm is designed to generate feasible solutions while satisfying all constraints. These solutions are fed into a population-based metaheuristic based on WOA, and then, a solution-based metaheuristic based on VNS is performed to further improve the best solution of WOA through local search operators.

The overall flowchart of the proposed combined H-WOA-VNS algorithm is shown in Fig. 2. Due to utilizing a knowledge-based heuristic algorithm, the search process of the metaheuristic algorithms starts from a set of near-optimal feasible solutions, rather than starting from random solutions, and thus, less iterations are required to effectively search among the search space. Moreover, due to applying the exploitation-specific local search VNS algorithm, the global best solution of the WOA would be further improved via the different local search operators stored in the VNS. To give more insight into the details, the pseudo-code of the proposed algorithm is provided in Algorithm 1.

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Algorithm 1. Proposed H-WOA-VNS algorithm for solving the PFSCM problem.

Input:
Model parameters of the PFSCM model
Output:
GBestSOL: optimized solution for the PFSCM model
Heuristic Phase:
for ($s \leq PopSize_{WOA}$)
Generate a feasible solution SOL(s) using the heuristic algorithm
Add SOL(s) into a population set, $s=\{1,2,\dots,PopSize_{WOA}\}$
end for
WOA Phase:
Considering the heuristic solutions as initial population of WOA
for ($s \leq PopSize_{WOA}$)
Evaluate the quality of SOL(s) using OF according to Eq. (10)
end for
for1 ($n \leq MaxIter_{WOA}$)
for2 ($s \leq PopSize_{WOA}$)
Update the values of p, l, and $\vec{a}$, and $\vec{A}$
if1 ($p < 0.5$)
if2 ($|\vec{A}| \geq 1$)
else if2
Update solution s via *encircling prey* according to Eq. (46)
end if2
else if1
Update solution s via *bubble-net attacking* according to Eq. (47)
end if1
Revise solution s, if it goes beyond the search space
Evaluate the quality of SOL(s) using OF according to Eq. (10)
Updating of the global best solution: GBestSOL
end for1
VNS Phase:
Considering GBestSOL as initial solution of VNS: $SOL^{current}$
for1 ($n \leq MaxIter_{VNS}$)
for2 ($l \leq NumLS_{VNS}$)
Generate SOL^{new} in vicinity of $SOL^{current}$ via local search operator l
Evaluate the quality of SOL^{new} using OF according to Eq. (10)
if $MoF^{new} < MoF^{current}$
Replace $SOL^{current}$ with SOL^{new}
Replace $MoF^{current}$ with MoF^{new}
Break for2
end if
end for2
Updating of the global best solution: GBestSOL
end for1
Output: Return the GBestSOL as the final optimized PFSCM model

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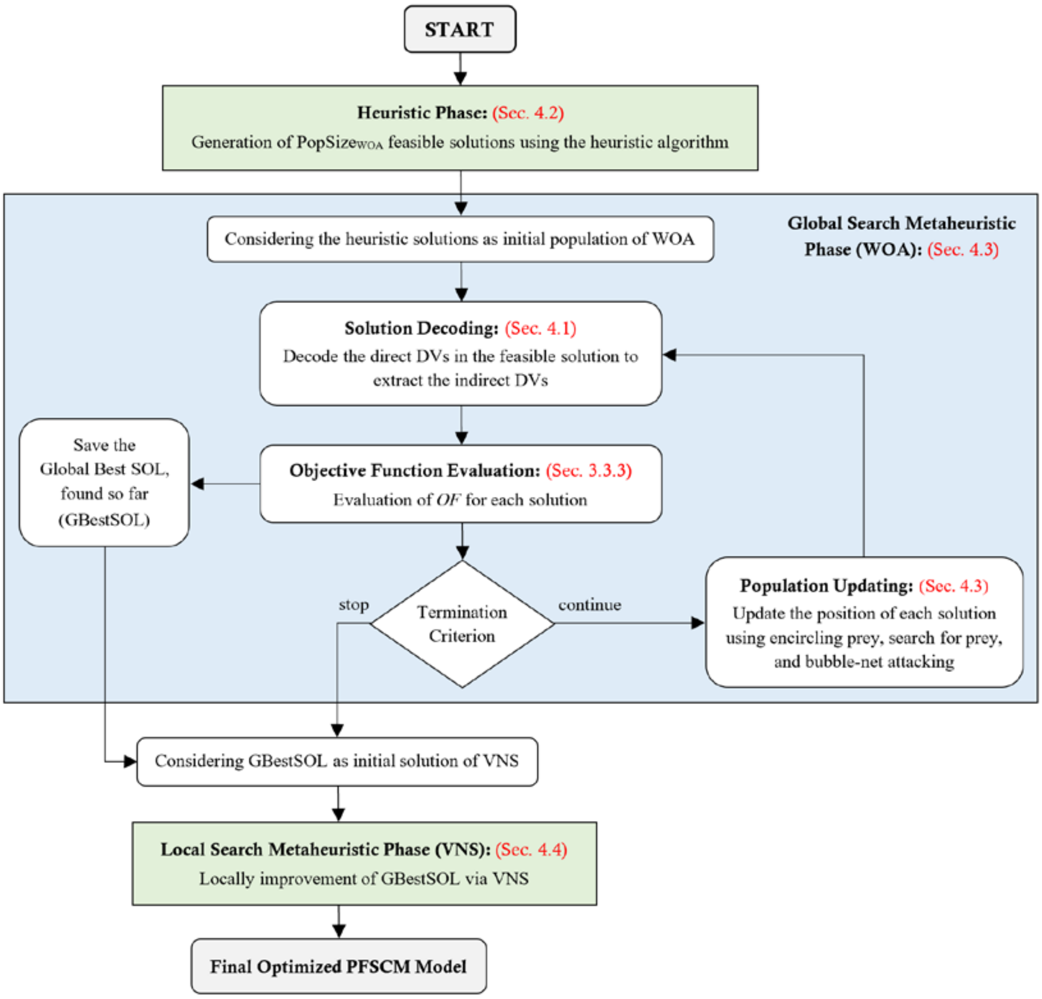

Figure 2. Overall flowchart of the proposed H-WOA-VNS algorithm.

4.1. Solution Representation

As mentioned above, we use direct and indirect DVs to encode and decode feasible solutions, respectively. Accordingly, a solution is represented via the direct DVs, while it is evaluated by decoding it and extracting the indirect DVs.

4.1.1. Solution Encoding

An example for the encoding of the direct DVs to solve the PFSCM model can be shown in Fig. 3. A solution, SOL, can be encoded via the direct DVs as multiple integer and permutation matrices as follows:

- SOL.P (P_{mpt}) is an integer matrix of dimension P×M×T which determines the amount of fertilizer p which is produced in manufacturer m at time t (per ton).
- SOL.R (R_{fpt}) is an integer matrix of dimension P×F×T to determine the amount of each fertilizer p delivered from the corresponding distribution center to each farm f at every time period t (per BS_p).
- SOL.PLM (PLM) is a permutation of M manufacturers to determine the ppriority of the manufacturers to order from different P-mines and suppliers.
- SOL.SLP (SLP_m) is a matrix of dimension M×(I+1) comprising M permutation vectors of I+1 P suppliers, i.e., each row m is a permutation of I mines plus the recycling center which determines the selection list of the different P-mines for the manufacturer m.
- SOL.SLS (SLS_m) is a matrix of dimension M×J, where each row m specifies the selection list of the different suppliers to supply raw materials for the manufacturer m.

- SOL.PLD (PLD) is a permutation of D distribution centers which determines the priority of them in ordering fertilizers from the different manufacturers.
- SOL.SLM (SLM_d) is a matrix of dimension D×M, where each row d is a permutation of M manufacturers to determine the selection list of the different manufacturers for the distributor d.

SOL.P: integer (per ton) P×M×T: ∀t

	1	2	3	4	...	M
SSP	14	35	24	15	...	45
TSP	27	15	30	6	...	12
MAP	34	8	32	12	...	42
DAP	47	25	22	14	...	21

SOL.SLP: M permutations of I+1 phosphate suppliers :

	1	2	3	4	...	I+1
1	6	1	4	5	...	8
2	2	8	6	9	...	3
⋮	⋮	⋮	⋮	⋮	...	⋮
M	4	5	1	2	...	7

SOL.R: integer (per BS_p) P×F×T: ∀t

	1	2	3	4	...	F
SSP	12	20	67	44	...	78
TSP	44	27	17	50	...	35
MAP	33	12	22	15	...	72
DAP	25	10	32	64	...	48

SOL.SLS: M permutations of J raw material suppliers :

	1	2	3	4	...	J
1	5	11	3	18	...	15
2	4	6	12	15	...	8
⋮	⋮	⋮	⋮	⋮	...	⋮
M	13	12	9	16	...	5

SOL.PLM: permutation of M manufacturers :

2	48	27	12	...	35

SOL.PLD: permutation of D distribution centers :

25	11	18	7	...	14

SOL.SLM: D permutations of M manufacturers :

	1	2	3	4	...	M
1	46	11	23	7	...	35
2	15	13	44	28	...	6
⋮	⋮	⋮	⋮	⋮	...	⋮
D	12	27	4	1	...	31

Figure 3. Encoding of the direct DVs into a feasible solution.

4.1.2. Solution Decoding

To evaluate a feasible solution, SOL, its direct DVs must be decoded into the indirect DVs including SP_{mrpt}, S_{mrt}, RP_t ,TD_{dpt},X^P_{imt}, X^R_{mt}, X^S_{jmrt}, X^M_{mdpt}, X^D_{dfpt}, X^F_{fpt}, Y^P_{imt}, Y^R_{mt}, Y^S_{jmrt}, Y^M_{mdpt}, Y^D_{dfpt}, Y^F_{fpt}, IP_{mpt}, ID_{dpt}, and IR_t , based on the direct DVs and other model parameters. To achieve this purpose, a backward mechanism from the demand nodes to the suppliers is applied to determine the value of the indirect DVs, as follows:

- *Decoding of farms-distribution centers DVs*: at the first step, X^D_{dfpt} and Y^D_{dfpt} are obtained according to the requested demands stored in R_{fpt} as:

$$X^D_{dfpt} = \begin{cases} 1 & if\ B_{fd} = 1\ and\ R_{fpt} > 0 \\ 0 & else \end{cases} \qquad \forall p, \forall d, \forall f, \forall t \tag{35}$$

$$Y^D_{dfpt} = \begin{cases} R_{fpt} BS_p & if\ B_{fd} = 1 \\ 0 & else \end{cases} \qquad \forall p, \forall d, \forall f, \forall t \tag{36}$$

- *Decoding of farms-recycling center DVs*: at the end of each time period, after delivering fertilizers Y^D_{dfpt} to the farm f and the irrigation procedure, the amount of P-leaching for fertilizer p can be estimated by multiplying the total recyclable fertilizers to the P-leaching coefficient of fertilizer p, according to Eq. (37). Then, the total amount of recycled phosphate at the end of time t is achieved according to Eq. (39). It should be emphasized that the lead time of phosphate recycling is one month, and consequently, the recycled P at time t can be transferred to the manufacturers in times t+1, t+2, and so on. To this end, the values of X^F_{fpt}, Y^F_{fpt}, and RP_t , are extracted.

$$Y^F_{fpt} = \sum_d \frac{\gamma_{fp}}{\mu_p} Y^D_{dfpt} X^D_{dfpt} B_{fd} \qquad \forall p, \forall f, \forall t \tag{37}$$

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$$X^F_{fpt} = \begin{cases} 1 & if\ Y^F_{fpt} > 0 \\ 0 & else \end{cases} \qquad \forall p, \forall f, \forall t \tag{38}$$

$$RP_t = \sum_f \sum_p \mu_p Y^F_{fpt} X^F_{fpt} = \sum_f \sum_p \sum_d \gamma_{fp} Y^D_{dfpt} X^D_{dfpt} B_{fd} \qquad \forall t \tag{39}$$

- *Decoding of distribution centers-manufacturers DVs*: based on the received demands by the farms, the total demand of each distribution center d for each fertilizer p at every time period t is calculated according to Eq. (40). Then, the different distribution centers are given one by one according to their priorities in PLD. For each distribution center d, different manufacturers according to their selection list in SLM_d are evaluated one by one to deliver fertilizers to the distributor d until satisfying its total demand TD_{dpt}. As a result, the values of TD_{dpt}, X^M_{mdpt} and Y^M_{mdpt} are extracted.

$$TD_{dpt} = \sum_f Y^D_{dfpt} X^D_{dfpt} B_{fd} \qquad \forall p, \forall d, \forall t \tag{40}$$

- *Decoding of manufacturers-raw material suppliers DVs*: at every time t, the demand of each raw material r for each manufacturer m for the production of fertilizer p is calculated by multiplying U^S_{rp} to the amount of the produced fertilizer p according to Eq. (41). Accordingly, the total demand of raw material r for each manufacturer m at every time t can be obtained by Eq. (42). Then, to satisfy the demand of the manufacturers, they are evaluated one by one based on their priorities in PLM. The manufacturer m is sourced by the different suppliers according to their selection list in SLS_m until satisfying the total demand of the manufacturer m for raw materails. As a result, S^S_{mrpt}, ST^S_{mrt}, X^S_{jmrt}, and Y^S_{jmrt}, are obtained.

$$S^S_{mrpt} = U^S_{rp} P_{mpt} \qquad \forall r, \forall p, \forall m, \forall t \tag{41}$$

$$ST^S_{mrt} = \sum_p S^S_{mrpt} \qquad \forall r, \forall m, \forall t \tag{42}$$

- *Decoding of manufacturers-phosphate suppliers DVs*: the phosphate demand of each manufacturer m to produce the fertilizer p at every time period t can be expressed as in Eq. (43), and then, the total phosphate demand for each manufacturer m at every time t is calculated according to Eq. (44). Similar to the supplier selection, to satisfy the phosphate demand of the manufacturer m, different P-mines as well as the recycling center (I+1 phosphate suppliers) are evaluated one by one based on their selection list in SLP_m until satisfying the phosphate demand of the manufacturer m. To this end, S^P_{mpt}, ST^P_{mt}, X^P_{imt}, X^R_{mt}, Y^P_{imt}, and Y^R_{mt}, are achieved.

$$S^S_{mrpt} = U^S_{rp} P_{mpt} \qquad \forall r, \forall p, \forall m, \forall t \tag{43}$$

$$ST^S_{mrt} = \sum_p S^S_{mrpt} \qquad \forall r, \forall m, \forall t \tag{44}$$

- *Decoding of inventories*: at the end of each time period t, the inventory of distribution centers, manufacturers, and recycling center, are updated according to Eqs. (18), (25) and (33), respectively.

4.2. Initialization Using a Heuristic Algorithm

The solution generation via the proposed heuristic algorithm is performed using a backward flow from the demand nodes (farms) to the suppliers, as follows:

- At first, SOL.R is constructed considering the P-uptake demand and minimum/maximum requested fertilizers by the farms. More specifically, the demand of farm f for the fertilizer p at every time period t, R_{fpt}, is randomly generated within [LP_{fpt},UP_{fpt}] to satisfy Eq. (12), while the total P-uptake from the different fertilizers fulfills the total demand given in Eq. (11).

- The total demand of each distribution center for all fertilizers at all time periods is calculated by the summation of the demands of the corresponding farms. Then, the priority list of the different distribution centers (SOL.PLD) is obtained by sorting them from the highest demand to the lowest demand.
- For each distribution center d, different manufacturers are sorted according to the total cost per unit of fertilizers (including purchasing and transportation costs), from the lowest to the highest cost. This procedure is repeated for all distribution centers to construct SOL.SLM.
- The amount of fertilizer p produced by manufacturer m at time t is considered to be a random value within [0.5×Cap_{mp}^{M}, Cap_{mp}^{M}], to construct SOL.P.
- The priority list of the manufacturers (SOL.PLM) is determined by sorting them from the most significant to the least significant according to their total production at all time periods.
- For each manufacturer m, the different raw material suppliers are sorted according to the total cost of purchasing and transportation from the lowest to the highest cost, and eventually, SOL.SLS is obtained. The same procedure is repeated for the I+1 phosphate suppliers (P-mines plus the recycling center) to construct SOL.SLP.

4.3. Global Search Using WOA

WOA is a swarm intelligence algorithm introduced by Mirjajili and Lewis [43], which mimics the hunting behavior of whales. In the proposed algorithm, the feasible solutions generated by the heuristic algorithm are considered as the initial population of the WOA. Then, at every iteration of the WOA, the quality of the current solutions is evaluated by the *OF* using Eq. (10), and eventually, the entire population is updated using *search for prey*, *encircling prey*, and *bubble-net attacking*. For the updating of the position of each whale w, a uniform random number p in [0,1] is generated. If p≥0.5, the solution is updated using the bubble-net attacking. Otherwise, a vector $\vec{A}$ is randomly generated as $\vec{A} = 2\vec{a}.\vec{r} - \vec{a}$, where the components of $\vec{a}$ are linearly decreased from 2 to 0 during the course of iterations, and $\vec{r}$ is a vector whose elements are randomly generated within [0,1]. If $|\vec{A}|$>1, the search for prey is applied; otherwise, the solution is subjected to be updated via the encircling prey. In the following, these updating operators are illustrated.

4.3.1. Search for Prey

If $|\vec{A}|\geq 1$, the whale is moved toward a random solution, which emphasizes more exploration (global search). Based on the search for prey, the whale w is updated as:

$$\mathrm{SOL}_w(t+1) = \mathrm{SOL}_{rand}(t) - \vec{A}.|2\vec{r}.\mathrm{SOL}_{rand}(t) - \mathrm{SOL}_w(t)| \tag{45}$$

4.3.2. Encircling Prey

At every iteration, it is assumed that the best solution found so far (GBestSOL) is in the vicinity of the global best solution (i.e., an optimal solution). Accordingly, if $|\vec{A}|$<1, the whale w tries to update its position toward the GBestSOL, as:

$$\mathrm{SOL}_w(t+1) = \mathrm{GBestSOL} - \vec{A}.|2\vec{r}.\mathrm{GBestSOL} - \mathrm{SOL}_w(t)| \tag{46}$$

4.3.3. Bubble-Net Attacking

The bubble-net attacking behavior can be modelled as a spiral equation between the current position of the whale w and GBestSOL, which simulates the helix-shaped movement of the whales. It can be formulated as:

$$\mathrm{SOL}_w(t+1) = |\mathrm{GBestSOL} - \mathrm{SOL}_w(t)|.\, e^{bl}\, cos(2\pi l) + \mathrm{GBestSOL} \tag{47}$$

where l is a random number within [−1,1], and b is a constant which defines the logarithmic spiral shape.

4.4. Local Search Using VNS

After termination of the WOA phase, its final solution is used as the initial solution of VNS, i.e., $SOL^{current}$=GBestSOL. In each iteration of VNS, a new solution, SOL^{new}, is constructed in the vicinity of the current solution, $SOL^{current}$, using multiple local search operators. If the quality of the new solution has been enhanced, the current solution is replaced with the new one; otherwise, it is not changed. In the case of integer matrices SOL.P and SOL.R, either Integer Swap (I-Swap) or Integer Exchange (I-Exchange) operator is applied, as illustrated in Fig. 4. Moreover, different permutation operators, including Exchange, Relocate, OrOpt, TwoOpt, and Reverse, may be performed on the permutation matrices. The permutation local search operators used in the VNS phase can be seen in Fig. 5.

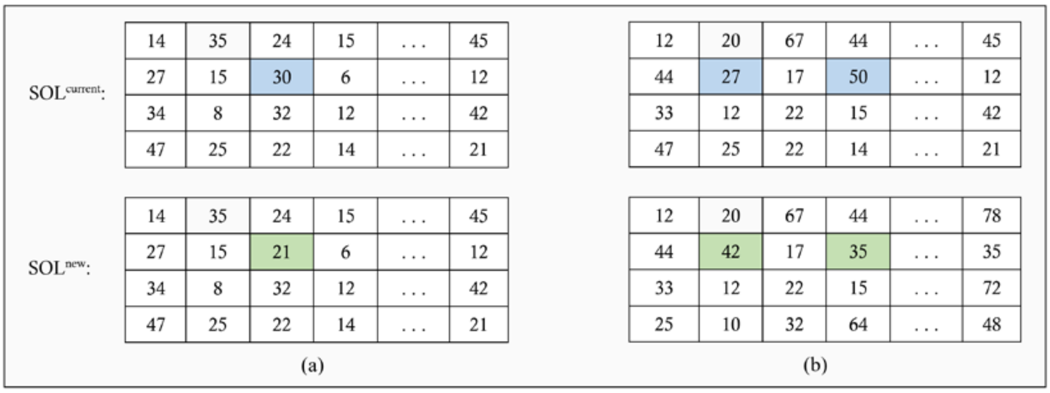

Figure 4. Encoding of the direct DVs into a feasible solution.

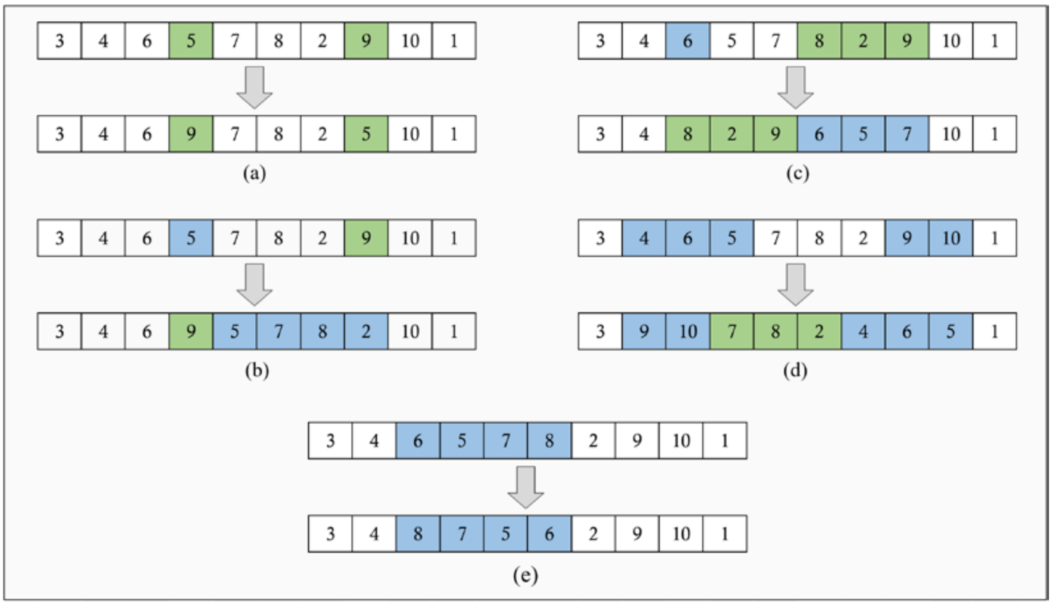

Figure 5. Permutation operators: (a) Exchange, (b) Relocate, (c) OrOpt, (d) TwoOpt, and (e) Reverse.

5. Experimental Results

Over the recent years, along with the increasing development in various industries, conducting academic research on optimizing and finding practical solutions to solve the SCM problems prospered more. According to existing literature, the scope of this paper is related to two main flows of the SCM: research related to the P-fertilizer supply chains and studies devoted to the solution methods, which are described in the following.

5.1. Case Study

To validate the H-WOA-VNS algorithm for solving the PFSCM model, a real case study based on the collected data from Iran has been used. Significant lands available for the cultivation in Iran have poor soil fertility. Due to the availability of natural gas reserves in Iran, there are many facilities for the production of the required raw materials for P-fertilizers. However, Iran faces with the low amount of P-mines, which results in a shortage of the required P to produce P-fertilizers. Four types of P-fertilizers in Iranian agriculture are used including SSP, TSP, MAP, and DAP. The composition of the main raw materials (P, A, SA, and PA) required to produce the four P-fertilizers (SSP, TSP, MAP, and DAP) in Iranian manufacturers are provided in Table 2. Moreover, the number of suppliers of raw material as well as their supplying capacities are reported in Table 3, where the P suppliers include two internal P-mines in Iran, two external suppliers in Iraq and Syria, and one recycling center in Iran.

The distribution centers of the PFSCM include 32 provinces in Iran. The annual demands of different distribution centers in terms of the total P-uptake as well as the lower and upper bounds of the required P-fertilizers are reported in Table 4. According to Tables 2-4, the required A, SA, and PA, can be satisfied via internal suppliers. However, the main problem in the Iranian P-fertilizers industry is that only about 30-40% of the need for P can be met through the domestic sources (including two internal P suppliers and one recycling center). Accordingly, the remaining requirement for the P may be imported from two external suppliers, i.e., other countries. However, there are more than 120 P-fertilizer manufacturers in Iran, with different production capacities. In this paper, we have chosen the 21 biggest P-fertilizers manufacturers in Iran with more than 2,000 tons production (monthly). The production capacity of the manufacturers is addressed in Table 5.

Table 2. Raw materials composition (%) for the different P-fertilizers.

P-Fertilizer	PA	P	A	P
SSP	0	64	0	64
TSP	34	40	0	40
MAP	51	0	12	0
DAP	47	0	23	0

Table 3. Capacity of the suppliers (ton/year).

Raw material	Total Capacity	Minimum Capacity	Maximum Capacity	Total Capacity
PA	870,000	12,000	240,000	870,000
SA	3,420,000	15,000	620,000	3,420,000
A	6,200,000	18,000	1,550,000	6,200,000
P	830,000	80,000	250,000	830,000

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Table 4. Demands of the distribution centers in terms of the total P-uptake and lower/upper bound on the required fertilizers (ton/year).

# Distributor	P-uptake	TSP		MAP		DAP	
		Lower	Upper	Lower	Upper	Lower	Upper
1	25820	9120	35820	10660	41580	5570	25380
2	23130	9980	33660	12860	41400	7200	23040
3	22180	10270	35280	7200	52020	5760	19080
4	17210	6910	30780	7780	31860	3840	13680
5	8610	3260	14220	3360	13500	2020	8460
6	10260	3460	15300	5470	22140	2590	8640
7	2810	1340	4860	1440	4680	670	2700
8	7260	1540	12600	4220	13320	1630	6480
9	5140	1920	7920	2780	8640	1440	4320
10	5810	2590	8460	1820	9900	1540	5940
11	41330	14500	70020	17860	66240	11620	42300
12	10760	3170	20160	4900	19980	2590	11160
13	52810	20740	97200	26400	92340	13630	47520
14	12180	6530	24120	4800	20880	2880	10980
15	4350	1730	5400	2300	7560	1250	3420
16	9810	4700	16020	5660	19800	2020	10440
17	37270	14590	68400	14780	59940	7010	32760
18	15000	5660	22500	5570	28080	3740	11700
19	4180	1920	6120	2020	8100	580	3780
20	19200	7680	32760	8830	33120	4320	19080
21	15410	6430	25380	7580	28440	2400	12960
22	24670	14300	46980	12770	46980	5470	26100
23	4530	2020	7380	1340	7920	1250	4860
24	25050	11140	40680	9310	52020	5470	22680
25	16460	6910	24840	7680	31860	3360	15300
26	20360	9120	34560	6620	30780	4420	17820
27	11090	4510	19980	4990	21060	2400	10800
28	9610	4030	13500	4510	17100	2400	8640
29	6830	3550	10440	3940	10980	2110	7740
30	19480	7100	33300	8930	36000	4220	18540
31	3560	1340	5580	1250	5940	860	3600
32	13840	6430	21240	7100	21600	2590	13860
Sum	506,010	208,490	845,460	226,730	905,760	118,850	473,760

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Table 5. Monthly capacity of the manufacturers for the P-fertilizer production (ton).

# Manufacturer	SSP	TSP	MAP	DAP
1	15000	5000	9100	11860
2	6660	13340	11000	14500
3	2500	2500	2560	3400
4	3340	3340	0	0
5	2500	1660	2480	3180
6	2500	2500	0	0
7	3340	1660	2520	3460
8	4160	0	0	0
9	8340	5000	8160	11320
10	0	16660	13380	23860
11	16660	0	21320	29360
12	0	16660	0	0
13	10000	2080	5640	9080
14	2400	4500	0	0
15	8340	16660	0	0
16	4160	840	3220	3840
17	4160	0	0	0
18	7500	2500	0	0
19	8340	8340	0	0
20	6000	6000	6360	8860
21	3340	1500	0	0
Sum	119,240	110,740	85,740	122,720

5.2. Settings

To set the parameters of the H-WOA-VNS algorithm, different options have been evaluated, and then, the best values and operators have been set for the final simulations. The controllable parameters of H-WOA-VNS is provided in Table 6. The number of iterations and population size in WOA have been considered as 500 and 70, respectively. To achieve the same number of objective function evaluations (NFE) in both WOA and VNS phases, the number of iterations in VNS has been set 10 times larger than that of in the WOA phase, i.e., to obtain $MaxIter_{VNS} \times NumLS_{VNS} = MaxIter_{WOA} \times PopSize_{WOA}$. The weights of the three objective functions Z_{EC}, Z_{CY}, Z_{PUE}, for the reported results in Sec. 5.3 and Sec. 5.4 have been considered as 0.5, 0.3, and 0.2, respectively. However, these weights would be changed in Sec. 5.5, to evaluate their effects on the different objective functions through a sensitivity analysis. The PFSCM model has been discussed and solved in T=12 time periods (months), i.e., one year. The other parameters of the model have been set according to the case study data, as summarized in Table 7.

Table 6. Parameters of the H-WOA-VNS algorithm.

Phase	Parameter	Value/Description
Heuristic	Maximum Iterations ($MaxIter_{WOA}$)	70 (=PopSizeWOA)
WOA	Population Size ($PopSize_{WOA}$)	500
	Population updating mechanisms	70
	Maximum Iterations ($MaxIter_{VNS}$)	Encircling prey, Search for prey, Bubble-net
VNS	Number of Local Search operators ($NumLS_{VNS}$)	5,000
	Local search operators	7
	Weight of economic cost (w_{EC})	I-Swap, I-Exchange, Exchange, Relocate,
OF weights	Weight of crop yield (w_{CY})	0.5
	Maximum Iterations ($MaxIter_{WOA}$)	0.3
	Weight of PUE (w_{PUE})	0.2

Table 7. Setting the PFSCM model parameters.

(a) Purchasing cost of raw materials ($/ton)

Cost	PA	P	A	P
Purchasing cost	310~370	60~70	20~25	80~95

(b) Producing cost of P-fertilizers ($/ton)

Cost	SSP	TSP	MAP	DAP
Production cost	110~130	120~150	210~250	230~280

(c) P-fertilizers coefficients (%)

Parameter	SSP	TSP	MAP	DAP
a_{fp}	0.26~0.32	0.29~0.35	0.42~0.47	0.46~0.52
β_{fp}	0.21~0.28	0.24~0.3	0.38~0.46	0.45~0.51
γ_{fp}	0.23~0.27	0.21~0.27	0.12~0.17	0.16~0.2
λ_p	0.53	0.38	0.64	0.62
μ_p	0.09	0.1	0.07	0.06

(d) Other parameters

Parameter	Value	Parameter	Value
BS_p	1 (ton)	TC_{im}^{PM}	1.5~2 ($/truck/km)
Truck size	25 (ton)	TC_{m}^{RM}	1.5~2 ($/truck /km)
RC	20 ($/ton)	TC_{jm}^{SM}	2~3 ($/truck /km)
IC_m^M	1.5 ($/ton/month)	TC_{md}^{MD}	2~2.5 ($/truck /km)
IC_d^D	2.5 ($/ton/month)	TC_{df}^{DF}	2~2.5 ($/truck /km)
IC^R	2 ($/ton/month)	TC_{f}^{FR}	2.5~3 ($/truck /km)

5.3. Results

5.3.1. Optimization Results

Because of the random-based nature of H-WOA-VNS (as well as other metaheuristics), it was performed in 10 successive runs for solving the PFSCM model. Considering the weights of the multi-objective function in Eq. (10) as w_{EC}=0.5, w_{CY}=0.3, and w_{PUE}=0.2, the obtained results for 10 runs are reported in Table 8, including the economic cost (Z_{EC}), the average crop yield (Z_{CY}), the average PUE (Z_{PUE}), the penalty function (PF), and the total objective function (OF). It can be seen in Table 8 that the difference between the worst and best solutions is 0.57% (OF_{worst} - OF_{best}=0.0028). Moreover, the standard deviation

(STD%) of the obtained OF in 10 runs is 0.19%. These results indicate that there is no significant difference between the results of the H-WOA-VNS algorithm in different runs. It ensures achieving similar results at every run, and helps us to trust to the obtained results of the algorithm by a single run on each new dataset.

The convergence of the H-WOA-VNS algorithm (on average over 10 runs) can be seen in Figs. 6 and 7. Figure 6 illustrates the best OF versus iterations of the WOA and VNS phases. To gain more insights about the convergence of the algorithm, Fig. 7 merges the two phases into a single diagram, representing the best OF versus NFE. The H-WOA-VNS algorithm starts by generating an initial population for WOA via the Heuristic algorithm, wherein the best solution has obtained OF=0.5491. In the beginning of the WOA phase, the algorithm's convergence is sharp, where the best OF decreases from about 0.55 to 0.51 in only 10% early iterations (50 out of all 500 iterations). This convergence speed is not only because of the nature of population-based metaheuristics, but also due to generating a set of near-optimal heuristic solutions in different positions of the whole search space. As WOA progresses, its convergence speed gradually decreases, and finally, the algorithm converges to OF=0.5014. By calling VNS to improve the global best solution of WOA through multiple local-search operators, a sudden shock in the convergence speed can be observed at early iterations of the VNS phase. It efficiently helps the H-WOA-VNS algorithm to further enhance the global best solution found by WOA, resulting in a 0.006 reduction in the OF and obtaining the final solution with OF=0.4954.

Table 8. Results of the H-WOA-VNS algorithm in 10 successive runs to solve the sustainable PFSCM model for the Case Study.

# Run	Total Cost (M$)	$\overline{Z_{EC}}$	$\overline{Z_{CY}}$	$\overline{Z_{PUE}}$	PF	OF
1	451.81	0.3012	0.3291	0.2789	0	0.4961
2	454.39	0.3029	0.33	0.278	0	0.4969
3	451.87	0.3012	0.3313	0.2778	0	0.4957
4	446.38	0.2976	0.3302	0.2781	0	0.4941
5	449.97	0.3	0.3317	0.2776	0	0.495
6	450.4	0.3003	0.3303	0.278	0	0.4954
7	448.04	0.2987	0.3303	0.2777	0	0.4947
8	453.47	0.3023	0.3298	0.2779	0	0.4966
9	449.1	0.2994	0.3295	0.2786	0	0.4951
10	446.55	0.2977	0.3293	0.2785	0	0.4944
Worst	454.39	0.3029	0.3291	0.2776	0	0.4969
Best	446.38	0.2976	0.3317	0.2789	0	0.4941
Mean	450.2	0.3001	0.3301	0.2781	0	0.4954
STD%	0.61	0.61	0.25	0.15	0	0.19

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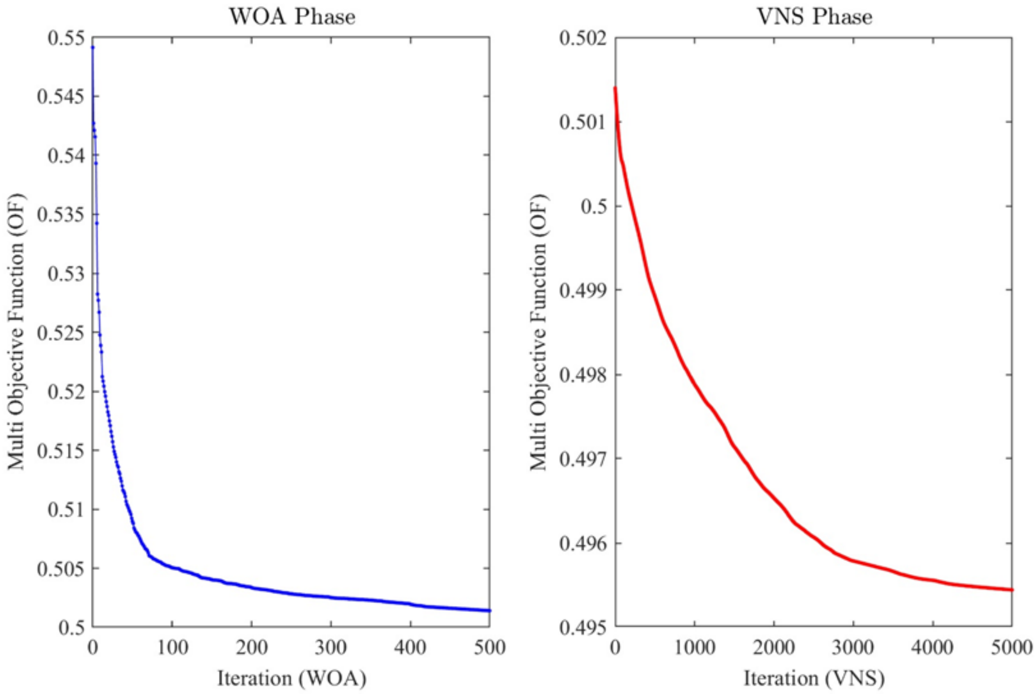

Figure 6. Best OF versus iteration in WOA and VNS phases: WOA phase (left), VNS phase (right).

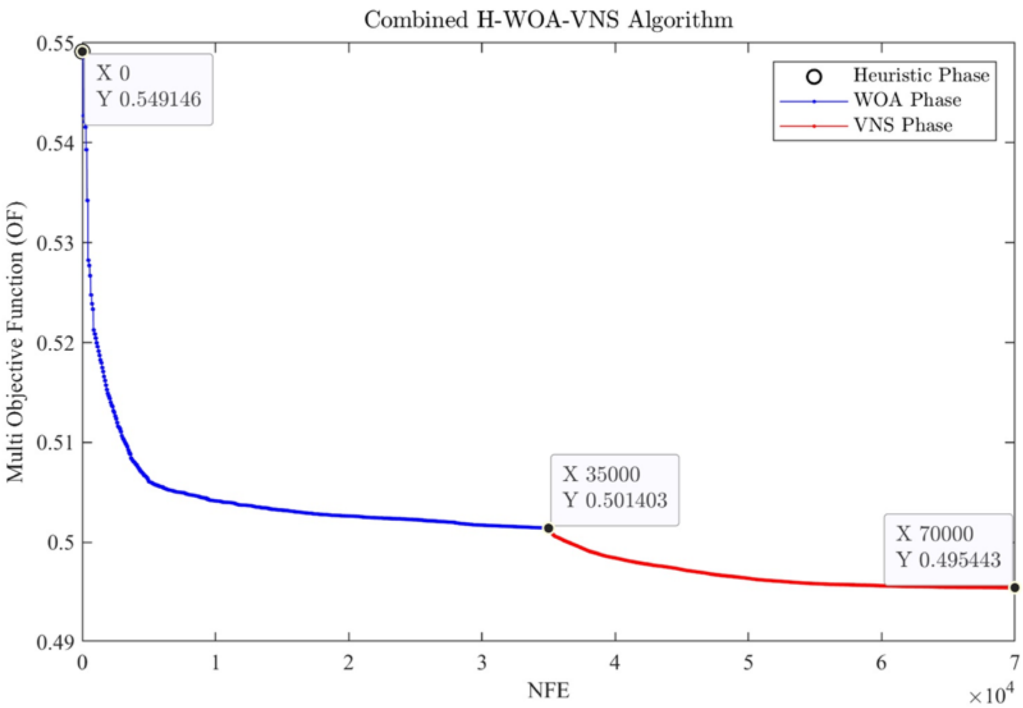

Figure 7. Convergence of the H-WOA-VNS algorithm in terms of the best OF versus NFE.

5.3.2. PFSCM Results

In the following, the results of the best solution among 10 runs (Run # 4 in Table 8) with OF=0.4941, are reported. The total economic cost 446.38 M$ includes six sub-economic costs as summarized in Table 9. The total productions of the P-fertilizers in all time periods for each manufacturer are provided in Table 10. According to Table 10, totally 346,001 tons SSP, 334,133 tons TSP, 229,976 tons MAP, and 185,799 tons DAP, have been produced by all manufacturers. The required raw materials supplied by the P-mines and raw material suppliers to produce the mentioned P-fertilizers are provided in Table 11.

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Considering the total P-fertilizers in the PFSCM for all time periods (sum of the initial inventories and the total production in all manufacturers), there are 416,001 tons SSP, 404,133 tons TSP, 279,976 tons MAP, and 255,799 tons DAP, which can be delivered to the distribution centers or held in the manufacturers' warehouses. The total delivered P-fertilizers to each distribution center can be seen in Table 12. Among the total P-fertilizers in all time periods, 409,332 tons SSP, 394,231 tons TSP, 274,317 tons MAP, and 248,570 tons DAP, have been delivered to all distribution centers, while 6,669 tons SSP, 9,902 tons TSP, 5,659 tons MAP, and 7,229 tons DAP, have been held in the manufacturers' warehouses at the end of the 12th time period. Table 13 summarizes the initial inventories, total productions, total P-fertilizers, total delivered P-fertilizers, and final inventories.

Table 9. Consumed raw materials (ton) for the production of the different fertilizers.

Cost Function	Cost (M$)
Purchasing cost of P from P-mines (C_{PP})	12.45
Purchasing cost of raw materials from suppliers (C_{PS})	118.68
Production cost of manufacturers (C_{PR})	178.73
Recycling cost of recycling center (C_{RC})	8.43
Inventory holding cost (C_{IH})	25.23
Transportation cost (C_{TR})	102.86
Total (Z_{EC})	446.38

Table 10. Monthly capacity of the manufacturers for the P-fertilizer production (ton).

# Manufacturer	SSP	TSP	MAP	DAP
1	62201	16814	23755	13767
2	20880	34684	24411	29242
3	3443	6301	7610	10408
4	10603	13513	0	0
5	9711	7485	7930	3633
6	6847	6915	0	0
7	12862	4020	4287	7042
8	11579	0	0	0
9	36142	19016	28027	4825
10	0	40030	27374	29133
11	55695	0	65218	52210
12	0	29818	0	0
13	24000	7365	20805	6362
14	4521	17704	0	0
15	10999	54914	0	0
16	10259	2594	5161	10004
17	14697	0	0	0
18	16603	8301	0	0
19	12711	35751	0	0
20	12264	24220	15398	19173
21	9984	4688	0	0
Total	346,001	334,133	229,976	185,799

Table 11. Raw materials composition (%) for the different P-fertilizers.

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P-Fertilizer	PA	P	A	P
SSP	0	128,020	0	221,441
TSP	113,605	0	0	133,653
MAP	117,288	0	27,597	0
DAP	87,326	0	42,734	0
Total	318,219	128,020	70,331	355,090

Table 12. Total delivered P-fertilizers (ton) and P-uptake (ton) in each distribution center.

# Distributor	Delivered P-Fertilizers				P-Uptake	
	SSP	TSP	MAP	DAP	Demand	Satisfied
1	22371	18384	13869	12442	25820	25990
2	18540	19411	11707	11309	23130	23536
3	17265	18403	12016	10496	22180	22531
4	13536	12662	10395	8235	17210	17542
5	6758	7088	4386	4443	8610	8806
6	7799	8365	5305	5578	10260	10572
7	2479	2193	1453	1503	2810	2957
8	5536	6286	3956	3563	7260	7503
9	4006	4292	2750	2434	5140	5216
10	4999	4402	3140	2711	5810	5888
11	33189	37554	19863	19200	41330	42001
12	8335	8105	6165	5133	10760	10825
13	40304	38313	31625	27526	52810	54315
14	8791	9092	6695	6465	12180	12234
15	3354	3489	2418	2236	4350	4490
16	7704	7757	4956	5027	9810	9891
17	31447	28598	21209	17344	37270	38173
18	13161	11212	8016	7174	15000	15278
19	3216	3375	2488	1963	4180	4301
20	15695	14540	10099	9543	19200	19373
21	13022	11981	7935	7303	15410	15518
22	21683	18118	12709	11919	24670	24872
23	3749	3460	2403	2272	4530	4615
24	19977	20235	12629	12229	25050	25165
25	13560	12526	10850	7775	16460	17480
26	15491	16723	11036	9630	20360	20515
27	8765	8025	6110	5628	11090	11164
28	8211	6572	5299	4861	9610	9732
29	5986	5814	3638	3424	6830	7265
30	16463	14592	9499	10407	19480	19795
31	3183	2641	1846	1712	3560	3616
32	10757	10023	7852	7085	13840	14017
Total	409,332	394,231	274,317	248,570	506,010	515,176

Table 13. Distribution of the different P-fertilizers (ton) in the system.

	SSP	TSP	MAP	DAP
Initial inventories	70,000	70,000	50,000	70,000

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Total productions	346,001	334,133	229,976	185,799
Total P-fertilizers	416,001	404,133	279,976	255,799
Total satisfied demands	409,332	394,231	274,317	248,570
Final inventories	6,669	9,902	5,659	7,229

5.4. Validation

In this section, at first, the proposed H-WOA-VNS algorithm is validated by comparing its results on some test problems against the exact method (Sec. 5.4.1). Then, the performance of H-WOA-VNS is justified by comparing the obtained results with its three components including the Heuristic, WOA, and VNS algorithms (Sec. 5.4.2), and also with three existing metaheuristics (Sec. 5.4.3).

5.4.1. Validation of H-WOA-VNS Against the Exact Method

To validate the optimality of H-WOA-VNS, its results on different PFSCM test problems as well as on the real case study are compared with an exact search. As mentioned above, the PFSCM (like other combinatorial SCMs), is an NP-hard problem, and thus, an exact method with an exhaustive search strategy is not applicable in terms of computational time complexity for the real-world SCM problems. However, to justify the H-WOA-VNS algorithm against the exact search method, we applied both techniques on five synthetic datasets (SDs) with small- and medium-sizes. The details of the synthetic and real PFSCM test problems are summarized in Table 14

The obtained results of performing the exact method as well as the proposed H-WOAVNS algorithm for solving the different PFSCM problems in 10 successive runs are summarized in Table 15. According to the obtained results, the running time of the exact algorithm exponentially grows with the size of the problem, and thus, it cannot solve medium- and large-size test problems (SD 5 and Case Study) in a reasonable time and faced with a low memory error. However, running time of the H-WOA-VNS algorithm increases almost linearly with the problem size, as the NFE of the algorithm is not changed and only the size of feasible solutions is increased. In terms of the optimization results, the obtained OF via H-WOA-VNS has a deviation of 0% to 0.13% from the optimal solution in four small-size datasets, that ensures achieving high-quality near-optimal solutions for the larger test problems such as the Case Study.

Table 14. Raw materials composition (%) for the different P-fertilizers.

Dataset	**Raw Materials (*R*)**	**Products (*P*)**	**P-mines (*I*+1)**	**Suppliers (*J*)**	**Manufacturers (*M*)**	**Distributors (*D*)**	**Demand Nodes (*F*)**	**Time Periods (*T*)**
SD 1	2	1	1	2	2	2	2	3
SD 2	2	1	1	3	3	3	4	3
SD 3	2	2	2	5	3	5	10	6
SD 4	3	3	2	7	5	10	10	6
SD 5	4	4	3	10	5	10	30	12
Case Study	4	4	5	52	21	32	565	12

Table 15. Monthly capacity of the manufacturers for the P-fertilizer production (ton).

Dataset	Optimal (Exact Search)		H-WOA-VNS		Error (%)
	OF	Time (s)	OF	Time (s)	
SD 1	0.4712	0.1	0.4712	32	0.000
SD 2	0.397	3.5	0.397	48	0.000
SD 3	0.4351	276	0.4352	126	0.023
SD 4	0.4613	37,650	0.4619	235	0.13
SD 5	N/A	N/A	0.4825	846	N/A
Case Study	N/A	N/A	0.4954	2725	N/A

5.4.2. Validation of H-WOA-VNS Against Other Heuristics and Metaheuristics

To find the effect of different stages of H-WOA-VNS, it was compared with its components (Heuristic, WOA, and VNS), when applying separately for solving the PFSCM model. For a fair comparison between the different methods, the number of iterations in WOA and VNS were set twice of those in the combined H-WOA-VNS algorithm, i.e., $MaxIter_{WOA}$=1000 and $MaxIter_{VNS}$=10,000, to obtain the same NFE=70,000 for all algorithms. Because of the random-based nature of the algorithms, each method was applied in 10 runs. The convergence of the different techniques in terms of the best OF versus NFE is shown in Fig. 8. Although WOA and VNS have a good convergence speed at the early 10% NFEs, then, they often trap into local optima points. To compare the proposed algorithm with the existing techniques for SCM, a population-based metaheuristic based on genetic algorithm (GA) [44], a solution-based metaheuristic based on simulated annealing (SA) [45], and a combined metaheuristic based on GA and SA (GLGASA) [38] have been also used for the PFSCM optimization considering our Case Study dataset. The OF obtained by the different techniques are provided in Table 16. The results demonstrate the effectiveness of the combined H-WOA-VNS method against other methods, in terms of the best and average results over 10 runs. Furthermore, the proposed algorithm obtains less STD%, which shows a higher reliability in a single run.

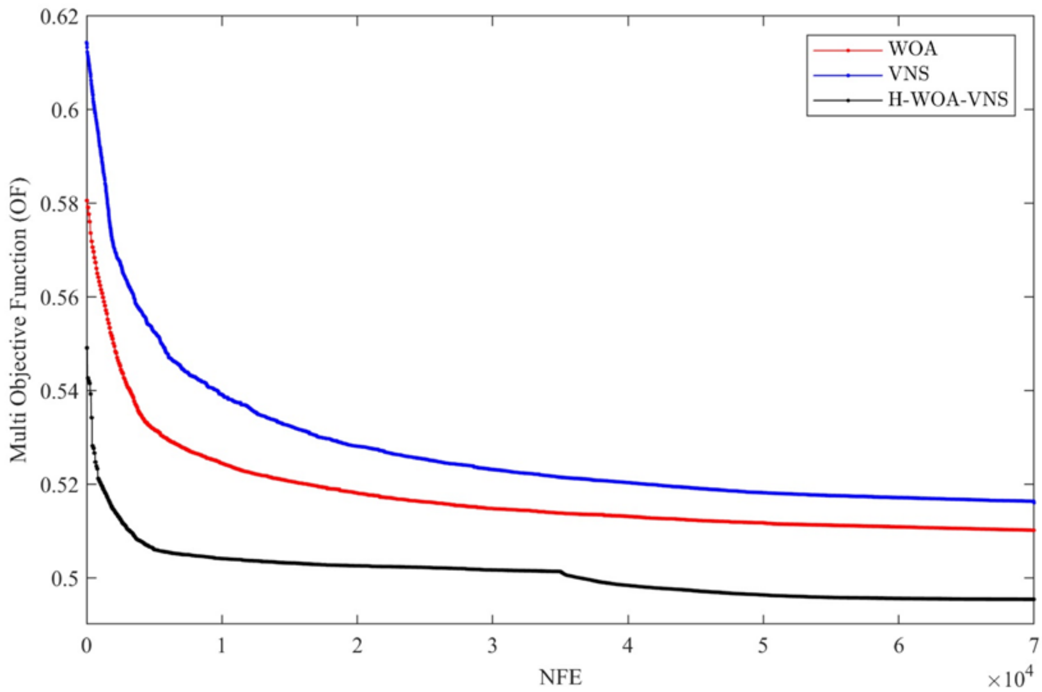

Figure 8. The best OF versus NFE obtained by WOA, VNS, and H-WOA-VNS.

Table 16. Comparison of the H-WOA-VNS algorithm against other techniques, over 10 runs.

# Run	Heuristic (Stage 1 of H-WOA-VNS)	WOA (Stage 2 of H-WOA-VNS)	VNS (Stage 3 of H-WOA-VNS)	GA [44]	SA [45]	GLGASA [38]	H-WOA-VNS (Proposed)
1	0.5495	0.5034	0.5283	0.5225	0.5127	0.5163	0.4961
2	0.5463	0.5267	0.5036	0.5344	0.5522	0.5222	0.4969
3	0.5571	0.502	0.5328	0.5107	0.5241	0.5213	0.4957
4	0.5412	0.5204	0.5078	0.5063	0.5245	0.5097	0.4941
5	0.5534	0.5156	0.5275	0.5263	0.5322	0.531	0.495
6	0.5651	0.4983	0.5224	0.5185	0.5167	0.5221	0.4954
7	0.5386	0.5066	0.5045	0.5122	0.542	0.5236	0.4947
8	0.5438	0.513	0.521	0.5332	0.5333	0.5021	0.4966
9	0.5444	0.5078	0.5019	0.5327	0.5191	0.5111	0.4951
10	0.5512	0.5083	0.5117	0.5278	0.5373	0.525	0.4944
Worst	0.5651	0.5267	0.5328	0.5344	0.5522	0.531	0.4969
Best	0.5386	0.4983	0.5019	0.5063	0.5127	0.5021	0.4941
Mean	0.5491	0.5102	0.5161	0.5225	0.5294	0.5184	0.4954
STD%	1.45	1.72	2.24	1.94	2.33	1.66	0.19

5.5. Discussion

Generally, decision makers may consider different preferences in designing supply chains, depending on the importance of different objectives. In the design of the PFSCM model in this paper, we have set the weights of the multi-objective function in Eq. (10) as w_{EC}=0.5, w_{CY}=0.3, and w_{PUE}=0.2. By changing the relative importance of the objective functions between 0 and 1 (while their summation remains fix equal to 1), we can find the effect of the different weights on the sub-objectives and the total objective function. Table 17 reports some samples of the sensitivity analysis, where the first row reports the default weights. For each sample, the model has been solved in 10 successive runs, and the average results are reported in Table 17. According to the obtained results, the first environmental objective function Z_{CY} has a huge conflict with the economic objective function. The first environmental objective function aims to improve crop yield, which needs more high PR processing P-fertilizers (MAP and DAP) than the low-medium PR processing P-fertilizers (SSP and TSP). It consequently increases the total economic cost, as high PR processing P-fertilizers have more purchasing and production costs. However, the second environmental objective Z_{PUE} has less conflict with the economic costs. To evaluate the effect of changing the weights of the multi-objective function in Eq. (10), we have changed the two environmental weights w_{CY} and w_{PUE} from 0 to 0.5 in steps of 0.1. Eventually, the weight of the economic objective function is considered as w_{EC}=1-(w_{CY}+w_{PUE}). By applying the H-WOA-VNS algorithm to solve the model for each combination, the normalized economic cost ($\overline{Z_{EC}}$) versus w_{CY} and w_{PUE} can be illustrated in Fig. 9. The figure confirms more conflict of the w_{CY} on the total economic costs.

To give an insight into the effectiveness of the proposed H-WOA-VNS algorithm against its components (Heuristic, WOA, and VNS) and the existing metaheuristics (GA, SA, and GLGASA), the worst, mean, and best obtained OF by the different methods over 10 successive runs are compared in Fig. 10. Moreover, improvement % of the H-WOA-VNS algorithm against other techniques is provided in Table 18. The results demonstrate the superiority of the proposed algorithm against the compared methods. It not only achieves the best results among all techniques, but also more importantly, it has a very less deviation than the other methods. The STD% of the H-WOA-VNS algorithm over 10 runs is only 0.19%, while it varies from 1.45% to 2.33% for the other methods.

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Table 17. Effect of the weights of the total objective function on the different sub-objectives.

w_{EC}	w_{CY}	w_{PUE}	$\overline{Z_{EC}}$	$\overline{Z_{CY}}$	$\overline{Z_{PUE}}$
0.5	0.3	0.2	0.3001	0.3301	0.2781
0.3	0.5	0.2	0.472	0.5644	0.2846
0.2	0.3	0.5	0.4346	0.4032	0.4328
0.5	0.5	0	0.4167	0.475	0.2153
0.5	0	0.5	0.2765	0.2387	0.585
0	0.5	0.5	0.5623	0.671	0.5012

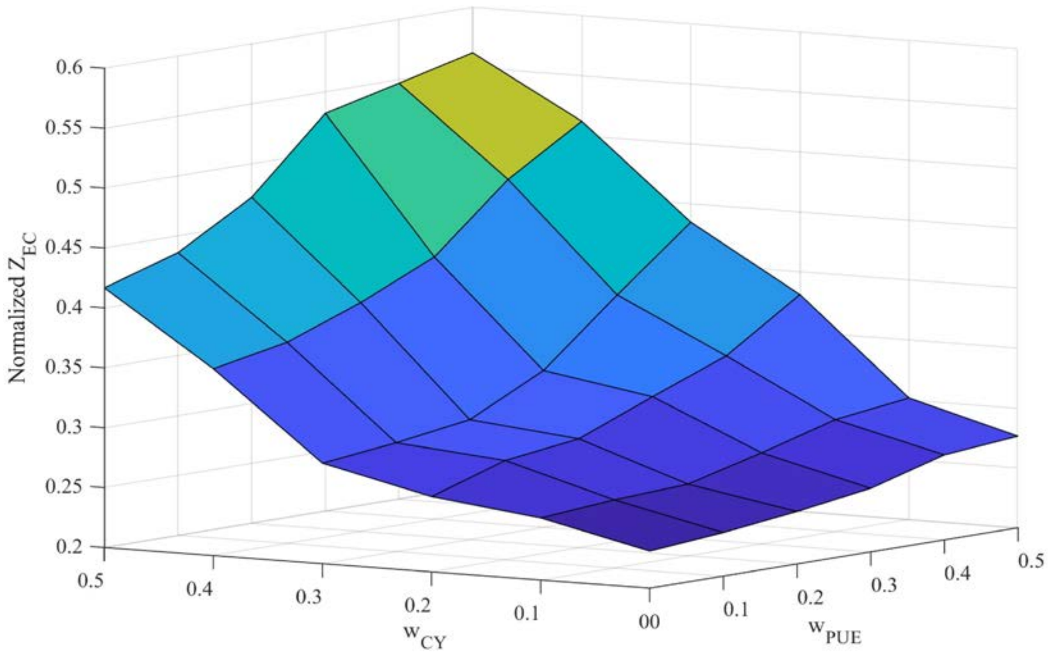
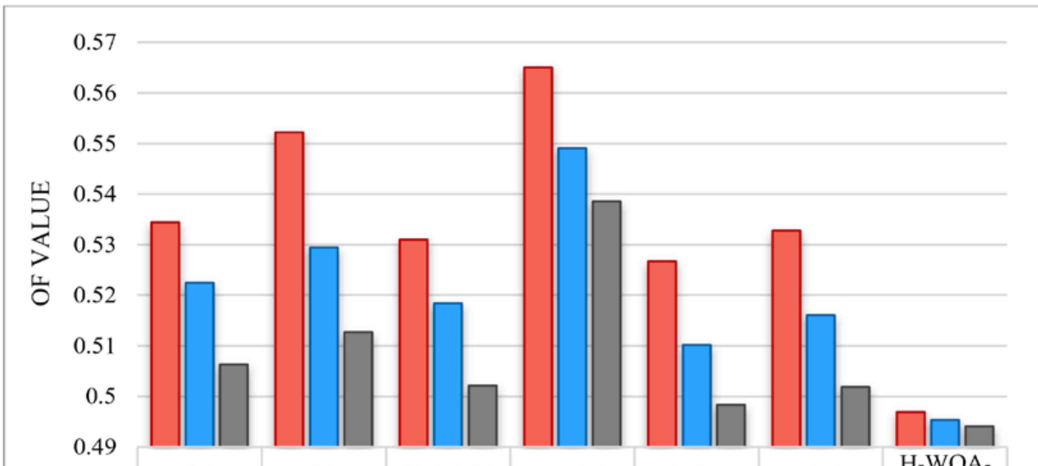


Figure 9. Sensitivity analysis of the environmental weights on the normalized economic cost.



	GA	SA	GLGASA	Heuristic	WOA	VNS	H-WOA-VNS
Worst	0.5344	0.5522	0.531	0.5651	0.5267	0.5328	0.4969
Mean	0.5225	0.5294	0.5184	0.5491	0.5102	0.5161	0.4954
Best	0.5063	0.5127	0.5021	0.5386	0.4983	0.5019	0.4941

Figure 10. Comparison of the worst, mean, and best results, obtained by the different methods.

Table 18. Improvement % of the H-WOA-VNS algorithm against other algorithms, in terms of the worst, best, mean, and STD% of the obtained OF over 10 runs.

Measure	GA	SA	GLGASA	Heuristic	WOA	VNS
Worst	7.02	10.01	6.42	12.07	5.66	6.74
Best	2.41	3.63	1.59	8.26	0.84	1.55
Mean	5.19	6.42	4.44	9.78	2.9	4.01
STD%	90.21	91.85	88.55	86.9	88.95	91.52

6. Conclusion

This study has introduced a new model for designing a close-loop renewable and sustainable supply chain management in the P-fertilizers industry, and the model has been justified using a real dataset in Iran. To solve the established model, a combined three-stage heuristic-metaheuristic algorithm with global- and local-search strategies, named H-WOA-VNS, has been introduced. At the first stage, it performs a problem-dependent heuristic to generate an initial population, in order to guide the metaheuristic algorithm to start from a set of near-optimal feasible solutions rather than starting from random solutions. At the second stage, a population-based metaheuristic with exploration and exploitation mechanisms is used to globally investigate the search space, and finally, an exploitation-oriented metaheuristic with multiple local search operators is used to further improve the quality of the global best solution found by the population-based metaheuristic algorithm.

Experimental results for five synthetic and a real case study have shown the validity and effectiveness of the proposed model and solution method. A comparison of the obtained results with other heuristic and metaheuristic methods has demonstrated the effectiveness of the proposed H-WOA-VNS algorithm to solve the sustainable P-fertilizer SCM model, which can also be applied to other SCM models. Due to a lack of attention in the literature to the sustainable P-fertilizer SCM from an operations research point of view, future researches are required by focusing on mathematically modeling and optimization techniques for the sustainable P-fertilizer SCM by utilizing other modeling and solution approaches. Moreover, uncertainties occurring in the system (parameters, objectives, and constraints) as well as the disruptions are also important issues which could be under consideration in future works.

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References

1. Huang, H., Li, J., Li, B., Zhang, D., Zhao, N., & Tang, S. (2019). Comparison of different K-struvite crystallization processes for simultaneous potassium and phosphate recovery from source-separated urine. Science of The Total Environment, 651, 787–795.
2. Nedelciu, C. E., Ragnarsdottir, K. V., Schlyter, P., & Stjernquist, I. (2020). Global phosphorus supply chain dynamics: Assessing regional impact to 2050. Global food security, 26, 100426.
3. Liang, H., Wang, C., Lu, X., Sai, C., & Liang, Y. (2022). Dynamic Changes in Soil Phosphorus Accumulation and Bioavailability in Phosphorus-Contaminated Protected Fields. International Journal of Environmental Research and Public Health, 19(19), 12262.
4. Barbosa, M. W. (2021). Uncovering research streams on agri-food supply chain management: A bibliometric study. Global Food Security, 28, 100517.
5. Kang, S., Kim, G., Roh, J., & Jeon, E. C. (2022). Ammonia Emissions from NPK Fertilizer Production Plants: Emission Characteristics and Emission Factor Estimation. International Journal of Environmental Research and Public Health, 19(11), 6703.
6. Shokouhifar, M. (2021). FH-ACO: Fuzzy heuristic-based ant colony optimization for joint virtual network function placement and routing. Applied Soft Computing, 107, 107401.
7. Al-Qaness, M. A., Ewees, A. A., Fan, H., & Abd Elaziz, M. (2020). Optimized forecasting method for weekly influenza confirmed cases. International Journal of Environmental Research and Public Health, 17(10), 3510.
8. Khairunissa, M., & Lee, H. (2022). Hybrid Metaheuristic-Based Spatial Modeling and Analysis of Logistics Distribution Center. ISPRS International Journal of Geo-Information, 11(1), 5.
9. Shokouhifar, M., & Ranjbarimesan, M. (2022). Multivariate time-series blood donation/demand forecasting for resilient supply chain management during COVID-19 pandemic. Cleaner Logistics and Supply Chain, 5, 100078.
10. Shehadeh, H. A., Mustafa, H. M. J., & Tubishat, M. (2022). A Hybrid Genetic Algorithm and Sperm Swarm Optimization (HGASSO) for Multimodal Functions. International Journal of Applied Metaheuristic Computing (IJAMC), 13(1), 1–33.
11. Ilinova, A., Dmitrieva, D., & Kraslawski, A. (2021). Influence of COVID-19 pandemic on fertilizer companies: The role of competitive advantages. Resources Policy, 71, 102019.
12. Rabbani, M., Molana, S. M. H., Sajadi, S. M., & Davoodi, M. H. (2022). Sustainable fertilizer supply chain network design using evolutionary-based resilient robust stochastic programming. Computers & Industrial Engineering, 108770.
13. Scholz, R. W., Ulrich, A. E., Eilittä, M., & Roy, A. (2013). Sustainable use of phosphorus: a finite resource. Science of the Total Environment, 461, 799–803.
14. Gong, H., Meng, F., Wang, G., Hartmann, T. E., Feng, G., Wu, J., Jiao, X., & Zhang, F. (2022). Toward the sustainable use of mineral phosphorus fertilizers for crop production in China: From primary resource demand to final agricultural use. Science of the Total Environment, 804, 150183.
15. Godde, C. M., Mason-D'Croz, D., Mayberry, D. E., Thornton, P. K., & Herrero, M. (2021). Impacts of climate change on the livestock food supply chain; a review of the evidence. Global food security, 28, 100488.
16. Yu, X., Keitel, C., & Dijkstra, F. A. (2021). Global analysis of phosphorus fertilizer use efficiency in cereal crops. Global Food Security, 29, 100545.
17. Withers, P. J. A., Sylvester-Bradley, R., Jones, D. L., Healey, J. R., & Talboys, P. J. (2014). Feed the crop not the soil: rethinking phosphorus management in the food chain. ACS Publications.
18. Gaffney, J., Bing, J., Sawyer, J., Byrne, P., Cassman, K., Ciampitti, I., ... & Warner, D. (2019). Science-based intensive agriculture: Sustainability, food security, and the role of technology. Global Food Security, 23, 236-244.
19. Chowdhury, R. B., Moore, G. A., Weatherley, A. J., & Arora, M. (2016). A novel substance flow analysis model for analysing multi-year phosphorus flow at the regional scale. Science of The Total Environment, 572, 1269–1280.
20. Gurevitch, J., Koricheva, J., Nakagawa, S., & Stewart, G. (2018). Meta-analysis and the science of research synthesis. Nature, 555(7695), 175–182.
21. Fakhravar, H. (2022). Combining heuristics and Exact Algorithms: A Review. ArXiv Preprint ArXiv:2202.02799.
22. Tirkolaee, E. B., Goli, A., Ghasemi, P., & Goodarzian, F. (2022). Designing a sustainable closed-loop supply chain network of face masks during the COVID-19 pandemic: Pareto-based algorithms. Journal of Cleaner Production, 333, 130056.
23. Sohrabi, M., Zandieh, M., & Afshar-nadjafi, B. (2021). A simple empirical inventory model for managing with demand differentiation. In Computational and Applied Mathematics (Vol. 2), 40(8),1-38.
24. Sohrabi, M., Zandieh, M., & Nadjafi, B. A. (2021). Dynamic demand-centered process-oriented data model for inventory management of hemovigilance systems. Healthcare Informatics Research, 27(1), 73-81.
25. Shokouhifar, M. (2021). Swarm intelligence RFID network planning using multi-antenna readers for asset tracking in hospital environments. Computer Networks, 198, 108427.
26. Rajabi Moshtaghi, H., Toloie Eshlaghy, A., & Motadel, M. R. (2021). A comprehensive review on meta-heuristic algorithms and their classification with novel approach. Journal of Applied Research on Industrial Engineering, 8(1), 63–89.
27. Farag, M. A., El-Shorbagy, M. A., Mousa, A. A., & El-Desoky, I. M. (2020). A new hybrid metaheuristic algorithm for multi-objective optimization problems. International Journal of Computational Intelligence Systems, 13(1), 920.
28. Chouhan, V. K., Khan, S. H., & Hajiaghaei-Keshteli, M. (2021). Metaheuristic approaches to design and address multi-echelon sugarcane closed-loop supply chain network. Soft Computing, 25(16), 11377–11404.
29. Gholizadeh, H., Goh, M., Fazlollahtabar, H., & Mamashli, Z. (2022). Modelling uncertainty in sustainable-green integrated reverse logistics network using metaheuristics optimization. Computers & Industrial Engineering, 163, 107828.

30. Karmakar, S., Kundu, A., & John, B. (2021). Optimizing a Supply Chain Network Using Metaheuristic for Pre and Post Pandemic Scenario. 2021 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 41–45.
31. Nath, M. P., Priyadarshini, S. B. B., & Mishra, D. (2022). Supply Chain Management (SCM): Employing Various Big Data and Metaheuristic Strategies. In Advances in Machine Learning for Big Data Analysis (pp. 145–165). Springer.
32. Nahavandi, B., Homayounfar, M., Daneshvar, A., & Shokouhifar, M. (2022). Hierarchical structure modelling in uncertain emergency location-routing problem using combined genetic algorithm and simulated annealing. International Journal of Computer Applications in Technology, 68(2), 150-163.
33. Wu, W., Zhou, W., Lin, Y., Xie, Y., & Jin, W. (2021). A hybrid metaheuristic algorithm for location inventory routing problem with time windows and fuel consumption. Expert Systems with Applications, 166, 114034.
34. Shokouhifar, M., & Pilevari, N. (2022). Combined adaptive neuro-fuzzy inference system and genetic algorithm for e-learning resilience assessment during COVID-19 pandemic. Concurrency and Computation: Practice and Experience, 34(10), e6791.
35. Liu, Y., & Chen, C. (2022). Improved RFM Model for Customer Segmentation Using Hybrid Meta-heuristic Algorithm in Medical IoT Applications. International Journal on Artificial Intelligence Tools, 31(01), 2250009.
36. Ghasemi Darehnaei, Z., Shokouhifar, M., Yazdanjouei, H., & Rastegar Fatemi, S. M. J. (2022). SI-EDTL: Swarm intelligence ensemble deep transfer learning for multiple vehicle detection in UAV images. Concurrency and Computation: Practice and Experience, 34(5), e6726.
37. Shokouhifar, M., Sabbaghi, M. M., & Pilevari, N. (2021). Inventory management in blood supply chain considering fuzzy supply/demand uncertainties and lateral transshipment. Transfusion and Apheresis Science, 103103.
38. Naderi, R., Shafiei Nikabadi, M., Alem Tabriz, A., & Pishvaee, M. S. (2021). Supply chain sustainability improvement using exergy analysis. Computers and Industrial Engineering, 154(January), 107142. https://doi.org/10.1016/j.cie.2021.107142.
39. Sohrabi, M., Zandieh, M., & Shokouhifar, M. (2022). Sustainable inventory management in blood banks considering health equity using a combined metaheuristic-based robust fuzzy stochastic programming. Socio-Economic Planning Sciences, 101462.
40. Sörensen, K. (2015). Metaheuristics—the metaphor exposed. International Transactions in Operational Research, 22(1), 3–18.
41. Esmaeili, H., Hakami, V., Bidgoli, B. M., & Shokouhifar, M. (2022). Application-specific clustering in wireless sensor networks using combined fuzzy firefly algorithm and random forest. Expert Systems with Applications, 210, 118365.
42. Shokouhifar, M., & Jalali, A. (2017). Optimized sugeno fuzzy clustering algorithm for wireless sensor networks. Engineering applications of artificial intelligence, 60, 16-25.
43. Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. Advances in Engineering Software, 95, 51–67.
44. Wang, K. M., Wang, K. J., & Chen, C. C. (2022). Capacitated production planning by parallel genetic algorithm for a multi-echelon and multi-site TFT-LCD panel manufacturing supply chain. Applied Soft Computing, 127, 109371.
45. Fathollahi-Fard, A. M., Govindan, K., Hajiaghaei-Keshteli, M., & Ahmadi, A. (2019). A green home health care supply chain: New modified simulated annealing algorithms. Journal of Cleaner Production, 240, 118200.