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A step forward in the management of multiple wastewater streams by using an ant colony optimization-based method with bounded pheromone

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ABSTRACT

Wastewater treatment systems (WTSs) have as an objective to efficiently treat the wastewater flows that they receive. Wastewater treatment plants (WWTP) process optimization is generally based on biological process optimization, which is usually related to the quantity and quality of the WWTP inflows. The inflow contributions sometimes destabilize the biological system due to flow and nutrient load limitations, with a higher impact in small and decentralized systems. Their management is a complex task due to the multiple constituents and different flows, but it should be the first step for a general, optimal and comprehensive optimization.

Ant colony optimization (ACO) has demonstrated the ability to solve these complex problems, as metaheuristic methodologies, using an iterative and probabilistic procedure. This work proposes to solve the treatment influent composition by using two ACO algorithms. Both algorithms apply bounded pheromone trails to resolve the failures in the search for an optimal solution limited by inflow constraints. The results present high efficacy in maximizing the total wastewater inflow that fulfils all the constraints and improving the WWTP management with different inflows and constraints.

1. Introduction

The control of the input characteristics into chemical and/or biological wastewater treatment facilities is a key factor in ensuring their efficiency. The different dynamics of flux generators can produce compositional fluctuations that introduce uncertainty into the process operation (Tchobanoglous et al., 2014), which should be avoided or minimized. The problem increases when the system is composed of multiple streams with different characteristics that contribute to a single influent of the treatment system.

Many authors have proposed deterministic or stochastic methodologies to optimize the operating conditions of processes that have dynamic inputs. Floudas (2000) studied the deterministic global optimization approaches, focusing on twice-differentiable constrained nonlinear optimization problems, mixed-integer nonlinear (MINLP) problems and locating all solutions of nonlinear systems of equations. For treatment or processing plants, the procedures aim to determine the optimal design and performance. One such strategy consists of optimizing the flows distribution or its costs for a superstructure, in which the flows' destination is a network of available treatments (or processes). Li et al. (2010) used deterministic methods. The authors developed a mixed-integer nonlinear programming (MINLP) for flows containing a single contaminant. Hernández-Suárez et al. (2004) used a superstructure decomposition and parametric optimization. Then,

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Nomenclature

BOD	biochemical oxygen demand
COD	chemical oxygen demand
C^r	concentration of pollutant r admissible in a wastewater treatment plant
C_i^r	concentration of pollutant r in storage for industrial activity i
I_i	industrial activity with $i \in \{1, \ldots, n\}$
H	heuristic information
k	generic subunits of wastewater storage with $L_i = kl_i$, specified as $k = 100$
K_i^j	coefficient related to the treatment saturation generated by the discharges
l_i	subunits of the wastewater storage for industrial activity i with $L_i = 100l_i$
L_i	volume of wastewater stored for industrial activity i
n	number of industrial activities
p_{dec}	probability of selecting an edge
p_{ij}	probability that industrial activity i achieves discharge V_i^j
P^r	price per unit of pollutant r
TN	total nitrogen
TP	total phosphorus
TSS	total suspended solids
T_i^r	peak coefficient related to the excess of concentration C_i^r in relation to its corresponding baseline value
V	admissible wastewater volume in the wastewater treatment plant
V_i	volumetric wastewater discharge obtained for industrial activity i
V_i^j	jth possible volume of wastewater discharge for industrial activity i corresponding to j 100(m^3). Note that $V_i^0 = 0$ for all activities
x_r	pollutant of the set (TSS, BOD, COD, TN, TP)
$\bar{X}_i^r$	baseline values for the concentration of pollutant r in industrial activity i
y_i^j	decision variable (0, 1) for discharging the jth volume of wastewater in industrial activity i
Z	cost of the total wastewater discharges
Z_1	volumetric cost of the total wastewater discharges
Z_2	cost of pollutant loads contained in the total wastewater discharges
Z_m	cost solution given by the mth ant
$Z_{\max}$	maximum value of the cost function

Greek letters

α	importance of the pheromone trails
β	importance of the heuristic information
ρ	coefficient of the pheromone persistence
τ_{ij}	trail of pheromone
$\tau_{\max}$	maximum value for the pheromone trail
$\tau_{\min}$	minimum value for the pheromone trail
ν	price per volumetric unit of wastewater discharge
ψ	weight of the cost of pollutant loads of the wastewater discharges

Li et al. (2015) developed MINLP for a set of contaminants and Nápoles-Rivera et al. (2012) and Tan et al. (2009) integrated recycle and reuse possibilities by using mixed integer linear and nonlinear programming, respectively. Halim et al. (2015) proposed the use of iterative procedures. They developed a genetic algorithm. In the same context, Hul et al. (2007) and Izquierdo et al. (2008) developed a particle swarm optimization (PSO). For existing facilities, the main objective is to improve the operating conditions by reducing the uncertainty through the use of predictive techniques. Thus, Shen et al. (2009) and Zeng and Liu (2015) proposed a model predictive control and an economic model predictive control, respectively. In contrast, Luus and Hennessy (1999) proposed a feed rate control using the Luus–Jaakola optimization procedure. Furthermore, Babu and Angira (2006) proposed the use of modified differential evolution; Fang et al. (2010) proposed an integrated dynamic model that combines a mechanistic model, a neural network model and a genetic algorithm approach; Huang et al. (2012) suggested an adaptive network-based fuzzy inference system; and Ráduly et al. (2007) and Wei and Kusiak (2015) proposed artificial neural networks. According to Hreiz et al. (2015), the real optimality of a computed solution is strongly dependent on the problem formulation. The authors noted that the temporary variations of wastewater characteristics in wastewater systems cannot be precisely known or estimated because of disturbances introduced by the wastewater generators (each component has its own dynamics, and the set can present multiple casuistics). In this context, the attainment of an optimal solution without mismatch between the real and the predicted behaviour constitutes a very difficult task.

However, recent proposals in the context of management systems for wastewater infrastructures (Cortés and Poch, 2009) and the online measurement of wastewater characteristics (Bonastre et al., 2005; Gruber et al., 2005) allow considering an approach based on real-time data. In this framework, a novel approach based on the mixing of multiple wastewater streams to compose the unique influent of a treatment system, as a constrained combinatorial optimization problem (specifically, a multidimensional knapsack problem), is possible (Verdaguer et al., 2012). According to Fréville (2004) and Voβ (2001), the complexity of this type of NP-Hard problems increases with the number of variables and the number of constraints. Under these conditions, it presents difficulties to be solved by using exact methods. Voβ (2001) recommended the use of heuristic and metaheuristic methods and Blum and Roli (2003) compared the metaheuristic methodologies for combinatorial optimization. The authors concluded with the good perspectives offered by metaheuristic methods based on a population, such as the ant colony optimization (ACO) algorithms, hybridized with basic local search-iterative improvement.

Hence, combinatorial optimization problems can be addressed by using ant colony optimization (ACO) algorithms (Dorigo et al., 1996, 1999; Dorigo and Stützle, 2004). The basic procedure of these algorithms is an iterative search conducted by a group of virtual ants to find an optimal solution. Virtual ants have a behaviour that mimics the conduct of real ants in the search for food. Obtaining a quality solution requires an exhaustive search of the entire search space. The convergence of the ACO algorithms to a global optimal solution was demonstrated by Gutjahr (2002) and Stützle and Dorigo (2002). For constrained problems, the algorithmic procedure could quickly generate large differences in the pheromone amounts left by ants. This can cause a stagnation of the solution (as the ants reach a local optimum and leave without exploring the rest of the search space). The use of bounded pheromone amounts is an important strategy to avoid this problem (Dorigo and Stützle, 2004; Stützle and Hoos, 2000). The procedure enables the achievement of an optimal solution even in large search spaces.

The Max–Min Ant System (Stützle and Dorigo, 2002; Stützle and Hoos, 1997, 2000) and the Hyper-Cube (Blum and Dorigo, 2004) are ACO algorithms that enhance the pheromone trails using bounds to ensure that the exploration strategy does not differ. For all iterations of ants, the pheromone values are in [Max, Min] in the Max–Min Ant System algorithm and in [0, 1] in the Hyper-Cube framework.

The Max–Min methodology has been applied to different types of computer problem (e.g., travelling salesman, quadratic assignment and vehicle routing problems) (Bullnheimer et al., 1999; Gambardella et al., 1999; Stützle and Hoos, 1997) and has demonstrated excellent results