# Multi-objective and multi-period optimization of regional timber supply network with uncertainty

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Multi-objective and multi-period optimization of regional timber supply network with uncertainty

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To assess the impacts of uncertainty and environmental objectives on the configuration of timber supply networks, we develop a generic multi-period, mixed-integer fuzzy linear programming model with demand uncertainty and two objectives of minimizing total transportation cost and GHG emissions. We then use the triangle fuzzy number method to define the uncertain demands and convert the model into its equivalent auxiliary crisp counterpart. To derive Pareto solutions more efficiently, the non-dominated sorting genetic algorithm (NSGA-II) is proposed to solve the model. Finally, we apply the model framework and solution method to a real-world case of regional timber supply in Fujian, China to demonstrate their applicability. The simulation results of the model show that trade-offs exist between total cost and GHG emissions and that the proper selection of the number and locations of distribution centers can help reduce both the cost and GHG emissions. Demand uncertainty and supply fluctuations across different time periods, can increase the cost and GHG emissions. Our empirical results provide useful insights into the design and management of regional timber supply networks, and our generic model is
applicable to the analysis of regional supply networks of other products or materials besides timber.

Keywords: Timber logistics network; Greenhouse gas emissions; Demand uncertainty; Pareto optimality; NSGA-II

1. Introduction

The design and management of regional timber supply networks often face common challenges of how to address multiple (often conflicting) objectives, multiple periods, supply dynamics and demand uncertainty. Although quite a few studies have explored each of these challenges separately, studies that consider all these three challenges simultaneously are limited. We attempt to shed light on the tradeoff between economic objective and environmental objective in timber supply network by developing a generic optimization model of regional logistics networks with multiple objectives, multiple periods, and demand uncertainty; proposing an effective solution method; and applying the modeling framework and solution method to a real case study of the regional timber supply network in Fujian, China.

Supply chain network design (SCND) addresses strategic and tactical decision-making in supply chain design and management theoretically and empirically (Eskandarpour et al. 2015). The decision problems dealt with by SCND mainly include facility location, customer demand allocation and distribution/transportation arrangements, among others (Farahani et al. 2014). In addition, practical aspects have been gradually incorporated into SCND models to
make the results more reasonable and useful. While a traditional SCND problem takes profit maximization or cost minimization as its single objective, recent studies have taken into account other criteria such as customer response time (Cardona-Valdés et al. 2011), social impacts (Devika et al. 2014), and environmental impacts (Mohammadi et al. 2014; Treitl and Jammernegg 2014). Specifically, some researchers have incorporated greenhouse gas (GHG) emissions into SCND problems and formed multi-objective optimization models (Fahimnia et al. 2015; Harris et al. 2011; Tang et al. 2013; Wang et al. 2011).

Furthermore, to better represent real-world scenarios, dynamic SCND problems have also been proposed, such as multi-period SCND (Cem et al. 2001; Dias et al. 2007; Melo et al. 2005, Jena et al. 2016) and SCND with uncertainty, especially demand uncertainty (Jouzdani et al. 2013). In order to depict uncertainties in the real world precisely, different methods have been used including fuzzy linear programming (Liang and Cheng 2009), stochastic programming (Santoso et al. 2005), risk decision (Vatsa and Jayaswal 2016) and robust optimization (Zetina et al. 2017).

Despite a lot of studies on general SCND (Farahani et al. 2014), research focused on forestry SCND has also been conducted due to specific characteristics of the supply chains in forestry. Troncoso and Garrido (2005) formulated a mixed-integer programming model to address the forestry SCND problem by integrating three decision problems: timber harvesting, facilities location and freight distribution. Their model had a single objective that was to minimize the present value of the total cost. Kanzian et al. (2009) examined a regional energy wood supply chain. They determined the locations of terminals from existing infrastructures through solving two consecutive transportation models with an objective to minimize the transportation cost. Although they considered combined flows (direct flows and flows
via terminals) in the network, the amount of materials handled via terminals was predefined. Flisberg et al. (2009) considered the transport part of the supply chain and addressed a routing problem of logging trucks to accomplish the transportation directly from forest/harvesting sites to processing plants with no terminal or depot included. The operational planning problem had a planning period of one day to one week. In order to find the most economically efficient way to transport logs in coastal regions of Norway, Nørstebo and Johansen (2013) developed an optimization model to determine the appropriate quay facilities by minimizing total system cost. Furthermore, different supply lines of forest biomass have been evaluated and estimated (Gronalt and Rauch 2007 and Kärhä 2011), but specific network configurations were not included in their aims. Vila et al. (2009) proposed a two-stage stochastic programming model to design production-distribution networks for lumber industry with stochastic demand. They used a sample average approximation method based on Monte Carlo sampling techniques for this stochastic program model.

Environmental factors have been considered in forestry SCND as well. For example, logistics systems especially the long-distance transportation contribute considerably to GHG emissions (Elhedhli and Merrick 2012). Abasian et al. (2017) proposed a generic value chain model of a single time period dealing with both strategic decisions including investments in new facilities and technologies and tactical decisions comprising backhaul transportation and fibre flows across the supply chain. Although the authors estimated the GHG emissions savings through using backhaul transportation, maximizing the overall profit of the value chain was the single objective of the proposed model.

With the growing interest in the production of biofuels from woody biomass, forest biomass-to-biofuel SCND problems were studied (Gunnarsson et al. 2004), and
more practical aspects were incorporated as well (Johnson et al. 2012; Shabani et al. 2013). Specially, to deal with uncertainties, Shabani et al. (2014) applied a two-stage stochastic programming model to optimizing the supply chain of a forest biomass power plant faced with the uncertainty in biomass availability. The bi-objective model proposed in that study investigated the tradeoff between risk and profit as well. Further, Shabani and Sowlati (2016) developed a hybrid model that combined robust optimization and stochastic programming to deal with the uncertainty of biomass quality and availability simultaneously, though their model had only one objective function of profit maximization.

Multi-objective optimization models are especially relevant to the design and management of supply chains in forestry, which often need to consider multiple conflicting objectives, for example, profit maximization (or cost minimization) and GHG emissions minimization (Cambero et al. 2016). Cambero and Sowlati (2016) developed a multi-objective mixed integer linear programming model that maximized the social benefit, net present value and GHG emissions saving potential of the supply chain of a forest-based biorefinery. They quantified social benefits of the supply chain by considering different impacts of the type and locations of new jobs. However, the impacts of network configuration on the tradeoffs between the objectives were not included in the studies mentioned above. Balaman et al. (2018) presented a bi-level decision support system for a renewable production supply chain. The system contained two consecutive multi-objective optimization models: the supply chain configuration design model (CDM) and the transportation network design model (TNM). Each of the models has three different objectives, respectively. As there were two models, transportation related emissions were excluded in the CDM, and facility-related emissions were excluded in the TNM. Mobtaker et al. (2018) proposed
a mixed-integer nonlinear goal-programming formulation to model the multi-objective planning problem in forestry, in which Nadir theory was employed as a scaling technique to deal with the multiple criteria including average unit purchasing and transportation cost, average volume per stem and average volume per hectare.

Although sometimes timber is transported directly from forest sites to processing plants (Flisberg et al. 2009), terminals are important in supply chain networks in forestry (Gautam et al. 2017). Furthermore, Sarrazin et al. (2018) showed that a regional logistic center comprising both a sorting yard and the sharing of transportation resources can bring higher profits as it can offer many opportunities for maximizing revenues and minimizing operational costs. Indeed, a timber supply network is a hybrid network where timber could bypass or go through the intermediate facilities (Malladi et al. 2018). As most of the transshipment models reported in the literature only consider indirect flows between supply points and demand points, where products must always transit through intermediate storage facilities, the hybrid network with combined flows is less explored in existing studies on SCND (Guastaroba et al. 2016). We consider a three-echelon hybrid network for timber supply, containing harvesting sites, logistics facilities, and wood processing plants. Traditionally, intermediate facilities in forest include wood yards, log yards, and satellite yards, etc. Wood yards are built mainly for timber processing activities, such as chipping, grinding and cellulose producing (Sreedevi et al. 2013; Spinelli et al. 2016). The log yard is set up to ensure the continuous operations in mill production through implementing activities like sorting, storage, and spreading truck loads (Beaudoin et al. 2012), and increase the residual value of forest restoration treatment by sorting and preprocessing logs as well (Chung et al. 2012). Satellite yards are employed during the supply process to reduce the length of the primary
materials supply cycle (Chan et al. 2008). In modern logistics practices, functions of logistics nodes have gradually expanded to include regional distribution, simple processing and other value-added services (Rao et al. 2015; Vila et al. 2006; Yang et al. 2013). It is the same in forest logistics operations. For example, Sarrazin et al. (2018) considered a sort and consolidation yard, offering more efficient sorting processes and the coordination of transportation, which was called logistics center in the study. Therefore, logistics facilities in our considered timber supply network are regarded as integrated ones, in which simple processing and distribution services are also provided as well as sorting, consolidation, chipping and storage, etc., and we call them logistics centers (LCs), following Sarrazin et al. (2018).

As SCND models developed in recent studies become closer to the real-world situations, the models have also become more complex, demanding longer computation time that is even beyond the capacity of commercial solvers using exact algorithms sometimes (Ng et al. 2018). Moreover, the derivation of Pareto solutions sets has encountered more difficulties (Cambero et al. 2016). In such cases, a good enough solution can be obtained much faster by applying heuristics algorithms. However, the application of heuristics algorithms, especially meta-heuristics in forestry SCND problems is rare.

In this study, we investigate an optimization problem of a hybrid regional timber supply network and develop a multi-objective and multi-period fuzzy mixed-integer programming model that incorporates carbon emissions along with cost minimization. Instead of focusing on a single optimal solution, we derive the Pareto solution sets that allow different decision-makers to find their best network configurations according to their preferences. Furthermore, timber supply dynamics and demand uncertainty are considered. Although we assume that the timber supply
is deterministic and do not consider uncertainty on the timber supply side, the
dynamics in timber supplies is described through using a multi-period model. By
contrast, the timber demand by downstream plants has higher degree of uncertainty.
Because of unavailability or unreliability of historical data as result of market
turbulences or technological innovations, stochastic programming may not be the
best choice to model demand uncertainty (Xu and Zhai 2010). In this regard, fuzzy
set theory would be a more reasonable method (Balaman et al. 2018). A fuzzy set is
characterized by fuzzy boundaries: each element belongs to a set with a certain
membership degree. Furthermore, triangular fuzzy numbers are considered as the
most suitable form to model market demands (Katagiri and Ishii 2000). Finally, to
overcome the difficulties in model solving caused by model complexity, we apply a
widely-used multi-objective optimization meta-heuristics algorithm, NSGA-II, to
solve the SCND problem.

The remainder of the paper is organized as follows. Section 2 gives the problem
description and presents the mathematical modeling formulation. Section 3 describes
the procedures to solve the optimization problem. Section 4 presents the
computational experiments and related discussion, and section 5 concludes.

2. Problem description and formulation

2.1 Problem description

We consider a regional timber supply network consisting of multiple supply points,
potential LCs and processing plants. Their locations are known. In each period, the
amount of timber unharvested in the previous period will be accumulated and added
to the current period with a certain loss rate denoted by the unharvest loss rate. This is
because the timber yield at the age of harvest is usually on or near the peak of the
curve representing the biological maturity of the forest (Kong and Rönnqvist 2014).
In this regard, loss is inevitable when harvesting is delayed.

The quantity of timber demand at a specific plant site in each period is uncertain
and depicted using a triangle fuzzy number. Fig. 1 shows the distribution of the
triangular fuzzy number $\tilde{f} = (f_1, f_2, f_3)$, where, $f_1$ and $f_3$ are the minimum and
maximum value, respectively, and $f_2$ is the most likely value.

![Fig. 1 The distribution of triangular fuzzy number $\tilde{f}$](image)

The potential locations of LCs need to meet some basic requirements/constraints,
such as conforming to the government’s land-use plan, having a large open field, and
being in close proximity to main roads. Each potential LC has a capacity limit and it
can be opened/ closed/reopened during the planning horizon at a certain cost. Timber
transferred by LCs incurs an extra cost including loading/unloading and simple
processing (e.g., sorting, barking and bucking) costs. Consequently, the weight loss of
timber defined in the model captures two situations resulting from handling processes
at LCs: one is the actual weight loss and the other is the increase in transportation
efficiency because of the more regular shape of timber after processing and/or
consolidation.

Additionally, the bark and residues are generally transported to thermal power
plants or wood-based panels (e.g., particle board, fiber board and MDF Board) plants,
from both LCs and timber processing plants. As separated transportation from every
plant is less efficient than integrated transportation from a LC, disposal of bark and
residues affects total cost and emissions in the same way as timber transportation.
Further, the effects are tiny given its small volume compared to timber. So, disposal of bark and residues is not considered in this study.

The optimization problem presented here is to simultaneously determine the number and locations of LCs from a given set of potential locations and the distribution of timber flows in the network in each period while considering both economic and environment objectives as well as the demand uncertainty. For modeling simplicity and without loss of generality, we do not consider different commodities of timber. Although there are many different product types including differences in species, quality and length, they can be transported by the same type of trucks.

Truck type is a major factor that affects the performance of a supply chain (Chan et al. 2016); however, secondary and tertiary roads are built for the specific purpose of transporting wood (Gautam et al. 2017). Due to the poor road and terrain conditions (e.g., unpaved, steep and narrow) in forest areas in southern China, vehicle types that can be used to access timber harvesting sites are limited. Therefore, our model defines different types of vehicles that depart from forest sites and LCs with different capacities, unit transportation costs, and GHG emissions rates, respectively.

Carbon emissions are associated with transportation activities and the operation of logistics facilities (LCs and plants) in the supply network. In terms of LCs and plants, we consider both fixed carbon emissions related to maintaining open LCs, which are basically determined by their sizes, and variable carbon emissions in proportion to the workload of processing at LCs or plants. For transportation emissions, we follow Chen et al. (2017), using the comprehensive emissions model developed by Barth and Boriboonsomsin (2009), which incorporates road and vehicle parameters. We do not include costs and emissions of the back empty trucks in this
study because the back and forth strategy can be incorporated by tuning the parameters related to the variable cost and emissions of every route.

2.2 The fuzzy programming model

In order to formulate the mathematical model, we introduce some notations that are depicted in Table 1.

Table 1 Notations

We propose the following fuzzy programming mathematical model for the multi-period regional timber supply network with uncertainty:

\[ \text{min} OBJ_1 = \sum_{t \in T} (CTT_t + CFL_t + CFF_t + CVP_t) \quad (1) \]

\[ \text{min} OBJ_2 = \sum_{t \in T} \left( \sum_{i \in H} \sum_{j \in K} w_{ij} c_{ijt} + \sum_{i \in L} \sum_{j \in K} E_{ij} x_{ijt} + \sum_{i \in L} \sum_{k \in K} F_{kijt} Z_{ktt} \right) \quad (2) \]

\[ \text{s.t.} \]

\[ CTT_t = \sum_{i \in H} \sum_{j \in K} w_{ij} c_{ijt} \quad \forall t \in T \quad (3) \]

\[ CFL_t = \begin{cases} \sum_{k \in K} FO_{kt} Z_{ktt} & t = 1 \\ \sum_{k \in K} (FO_{kt} Z_{ktt} (1 - Z_{k(t-1)}) + FC_{kt} Z_{k(t-1)} (1 - Z_{ktt})) & t > 1 \end{cases} \quad (4) \]

\[ CFF_t = \sum_{k \in K} F_{ktt} Z_{ktt} + \sum_{i \in L} \sum_{k \in K} x_{ijt} g_{kt} \quad \forall t \in T \quad (5) \]

\[ CVP_t = m_{ij} \sum_{i \in H} x_{ijt} \quad \forall j \in K \setminus P, t \in T \quad (6) \]

\[ x_{ijt} \leq w_{ijt} Q_1 \quad \forall i \in H, j \in P \setminus K \quad (7) \]

\[ x_{ijt} (1 - \varphi_j) \leq w_{ijt} Q_2 \quad \forall i \in K, j \in P \quad (8) \]
\[ r_i(t-1)(1-\eta_i) + S_i - \sum_{j \in K \cap P} x_{ijt} = r_i \quad \forall i \in H, t \in T \]  

\[ \sum_{i \in H} (\sum_{j \in H} x_{ijt} + \sum_{i \in P} x_{ijt}) \geq \bar{N}_{jt} \quad \forall j \in P, t \in T \]  

\[ \sum_{i \in H} (\sum_{j \in H} x_{ijt} + \sum_{i \in P} x_{ijt}) \leq \bar{N}_{jt} \quad \forall j \in P, t \in T \]  

\[ \sum_{j \in H} x_{ijt} \leq V_i Z_{it} \quad \forall i \in K, t \in T \]  

\[ \sum_{i \in H} \sum_{j \in H} x_{ijt} (1-\varphi_j)(1-\gamma)^{t-1} \geq \sum_{i \in H} \sum_{j \in P} x_{ijt} \quad \forall j \in P, t \in T \]  

\[ x_{ijt} \geq 0 \quad \forall i \in H, j \in K \cap P \]  

\[ r_i \geq 0 \quad \forall i \in H \cap K, t \in T \]  

Non-negative integer \( w_{ijt} \) \( \forall i \in H \cap K, j \in K \cap P, t \in T \)  

\[ Z_{it} \in \{0,1\} \quad \forall k \in K, t \in T \]  

OBJ\(_1\) minimizes the total cost of the network in the planning horizon. OBJ\(_2\) measures the CO\(_2\) emissions of the network. It contains three parts: the first part is emissions caused by transportation, the second part is caused by processing, and the third part is the fixed carbon emissions of LCs in operation.

Unlike most previous studies in which transportation cost was calculated using the cost per unit flow of product, we use the number of truckloads required, because a fixed cost occurs when activating a trip or dispatching a truck. Although this increases the complexity of the model due to the added decision variable, it is more reasonable since it conforms to the transportation cost in practice and it helps to improve the vehicle loading rate to some extent as well.

The cost of each period contains four parts calculated by Expressions (3)-(6) respectively. Constraints (7) and (8) define the relationships between timber flows and
trucks’ trips. Equations (9) restrict the timber volume at supply points in each period. Constraints (10) and (11) state the accumulated lower and upper bound of demands, respectively. Constraints (12) is the capacity constraint of LCs. Constraints (13) ensures that the accumulated amount of timber flowing out of a LC is no more than that flowing into it in any period. Finally, constraints (14)-(17) impose constraints on decision variables.

### 2.3 The equivalent auxiliary crisp model

The proposed model is a multi-objective fuzzy programming model. To solve it, this model is converted to its equivalent crisp counterpart using the credibility-based chance constrained programming, which is a computationally efficient fuzzy mathematical programming approach (Liu and Liu 2002).

Firstly, for equations (10) and (11) containing fuzzy parameters, if a confidence level of demand point $j$, denoted by $\alpha_j$, is given, they can be modified to (16) and (17) respectively:

$$\text{Cr} \left\{ \sum_{l=1}^{L} \left( \sum_{i \in H} x_{ijl} + \sum_{i \in k} x_{ijl} \right) \geq \tilde{N}_{ij} \right\} \geq \alpha_j \quad \forall j \in P, t \in T \quad (16)$$

$$\text{Cr} \left\{ \sum_{l=1}^{L} \left( \sum_{i \in H} x_{ijl} + \sum_{i \in k} x_{ijl} \right) \leq \tilde{N}_{ij} \right\} \geq \alpha_j \quad \forall j \in P, t \in T \quad (17)$$

Secondly, based on credibility measure, they are further converted to the equivalent crisp forms. Let $\xi$ be a triangular fuzzy number $[\xi = (f_1, f_2, f_3), f_1 \leq f_2 \leq f_3]$, and the membership function $\mu_x$ is formulated as:

$$\mu_x (x) = \begin{cases} 1 & \text{if } x \leq f_1 \\ \frac{x - f_1}{f_2 - f_1} & \text{if } f_1 < x \leq f_2 \\ \frac{f_3 - x}{f_3 - f_2} & \text{if } f_2 < x \leq f_3 \\ 0 & \text{otherwise} \end{cases}$$
Let $r$ be a real number. The possibility, necessity and credibility of $\{\xi \geq r\}$ are defined by equations (19), (20) and (21), respectively (Liu and Liu 2002).

$$\text{Pos}\{\xi \geq r\} = \sup_{u < r} \mu(u)$$  \hspace{1cm} (19)

$$\text{Nec}\{\xi \geq r\} = 1 - \text{Pos}\{\xi < r\} = 1 - \sup_{u < r} \mu(u)$$  \hspace{1cm} (20)

$$\text{Cr}\{\xi \geq r\} = \frac{1}{2} (\text{Pos}\{\xi \geq r\} + \text{Nec}\{\xi \geq r\})$$  \hspace{1cm} (21)

Noteworthy, since $\xi$ is a triangular fuzzy number with the membership function defined in equation (18), the corresponding credibility measures are as follows:

$$\text{Cr}\{\xi \geq r\} = \begin{cases} 1, & r \leq f_1 \\ \frac{2f_2 - f_1 - r}{2(f_1 - f_2)}, & f_1 < r \leq f_2 \\ \frac{f_2 - r}{2(f_3 - f_2)}, & f_2 < r \leq f_3 \\ 0, & r \geq f_3 \end{cases}$$  \hspace{1cm} (22)

$$\text{Cr}\{\xi \leq r\} = \begin{cases} 0, & r \leq f_1 \\ \frac{r - f_1}{2(f_2 - f_1)}, & f_1 < r \leq f_2 \\ \frac{r - 2f_2 + f_1}{2(f_3 - f_2)}, & f_2 < r \leq f_3 \\ 1, & r > f_3 \end{cases}$$  \hspace{1cm} (23)

Therefore, based on Lemma 1 (see Appendix A.), equations (10) and (11) are modified to equations (24) and (25), respectively:

$$\sum_{l=1}^{L} (\sum_{i \in H} x_{ij} + \sum_{i \in k} x_{ij}) \geq \sum_{l=1}^{L} [2(1 - \alpha_j) \cdot \mu_{j}^{-} + (2\alpha_j - 1) \cdot \mu_{j}^{+}] \quad \forall j \in P, t \in T$$  \hspace{1cm} (24)
where, \( \alpha_j \) is the confidence level of demand point \( j \) (0.5 < \( \alpha_j \) ≤ 1); \( \mu_{j1}^- \) and \( \mu_{j1}^+ \) are the lowest values of upper and lower demands for plant \( j \), respectively; \( \mu_{j2}^- \) and \( \mu_{j2}^+ \) are the most likely values of upper and lower demands for plant \( j \), respectively; \( \mu_{j3}^+ \) and \( \mu_{j3}^- \) are the highest values of upper and lower demands for plant \( j \), respectively.

Accordingly, the demand uncertainty in the multi-period regional timber supply network is converted to its crisp equivalent forms by determining the confidence level for demand points.

It is worthy to note that the proposed model is a non-linear programming model that is hard to solve using an exact algorithm. Due to multiple periods, equation (4) used to calculate the fixed cost of LCs is non-linear. Furthermore, the relationships between the objectives and the decision variables (timber flow) are also non-linear. In the calculation of transportation cost and GHG emissions, the units (in trip) are different from those of timber flows (in m\(^3\)). Consequently, the transportation sub-problem in the optimization of the multi-period regional timber supply network is a step fixed-charge one that is a “NP-super hard” (Non-deterministic Polynomial-time) problem due to the step function structure of the objective functions. “NP-hard” means that the computational time to obtain exact solutions increases in a polynomial fashion and very quickly becomes extremely long as the size of the problem increases, and “NP-super hard” means a much “higher degree” of polynomial complexity (Kowalski and Lev 2008). Therefore, it is time consuming to derive the Pareto frontier of this problem using an exact algorithm. In this study, the elitist non-dominated sorting genetic algorithm, NSGA-II is used.
3. The solution method

NSGA-II, developed by Deb et al. (2002), is one of the representative evolutionary algorithms for solving multi-objective optimization problems, and has been modified and applied to various fields successfully (Lin and Song 2015; Moravej et al. 2015). The NSGA-II solution strategy is mainly characterized by non-dominated sorting procedure and crowding distance index which help to find better spread of solutions and better convergence near the true Pareto-optimal front with lower computational complexity. The non-dominated sorting assigns a non-dominated rank to each solution. For an $n$-objective problem, a solution is said to dominate another solution if it is better in all the $n$ objectives than the other and a non-dominance solution is one for which any improvement in one objective can only take place if at least one other objective worsens (Messac et al. 2003). If a solution is not dominated by any other solution, it is put into the first rank. Within a population, the solution with a higher rank level has a higher priority in the following operators: selection and evolution.

Crowding distance is an index of diversity, which measures the proximity of a solution to its nearest neighbor. When solutions have the same non-dominated rank, a solution with smaller value of crowding distance is more crowded, and the less crowded solution is with higher preference.

The NSGA-II procedure applied in this paper is described briefly in the following:

Step 1: An initial population of solutions is randomly generated and placed in set $P$. The values of objectives are calculated, and then the members of the population are sorted using the non-dominated sorting procedure, and crowding distances are calculated as well.

Step 2: Crossover operation is performed on $P$, based on the binary tournament
selection operator. The chromosomes are randomly paired first and the one with higher priority is selected, then the crossover operation is implemented on every two selected chromosomes to generate two child-chromosomes. This process is repeated until the number of the child-chromosome becomes equal to the number of initial population. After that, the mutation operation is performed on child-chromosomes with a probability to help maintaining population diversity. Then children solutions are generated and placed in set $Q_t$.

Step 3: $P_t$ and $Q_t$ are combined to form set $R_t$. Evolution operator is performed on $R_t$ based on non-dominated rank and crowding distance to accelerate convergence without losing diversity. In this way, the next parent population is formed.

Step 4: The steps 2 and 3 are repeated for the required number of generations.

3.1 Representation

Chromosome representation affects the effectiveness and efficiency of the genetic algorithm deeply (Jo et al. 2007). For the problem addressed in this study, a solution contains at least two decision aspects: locations of LCs and distribution of timber flows. However, the distribution of timber flows is comprehensive, because the timber supply may comprise one or two stages. Hence, the solution for timber transportation is divided into two subsets: transportation from supply points and LCs to demand points and that from supply points to LCs.

We use the revised determinant encoding developed by Wang and Hsu (2010), which has been proved effective when solving a multi-stage SCND problem (Yao and Hsu, 2009). Fig. 2 is an example of our chromosome presentation in a particular time-period for a network that has four suppliers, four potential LCs and two plants. It has three parts: part 1 refers to the decision of opening LCs, and part 2 and 3 are the
two stages of transportation decisions mentioned above. Part 2 represents the transportation decision from supply points and LCs to demand points, and Part 3 represents the transportation decision from supply points to LCs.

Fig. 2 A part of chromosome of a single time-period

When the chromosome is decoded, which LCs to open in every period is determined according to the first part of the chromosome. For the chromosome in Fig. 2, only LC 1 is open in the time-period. Then the available supply of the open LCs is determined accordingly. If a LC is not open, its supply in the first stage of transportation and demand in the second stage of transportation are both zero. Otherwise, the supply volumes of open LCs are supposed to be their capacities respectively and the transportation decision in the first stage is decoded. Then, the amount of timber flowing out of an open LC to plants determines the demand of the LC in the second stage (from supply points to LCs) of the transportation decision.

3.2 Genetic operators

After initialization is done, crossover and mutation operations are performed. They are applied to the three parts of the chromosome separately, and two-point crossover and random mutation are adopted in this study.

4. Case study

This section describes the numerical experiments conducted with a real-world case. We consider a regional network optimization problem in Jiangle, Fujian province, China. Based on the amount of annual production and flow direction of each wood
landing location in the forest zones, seven supply points are chosen: Yufang, Huangtan, Guangming, Nankou, Dayuan, Wanquan and Dengfang. The total supply of the seven locations accounts for over 80% of the local timber demand. Similarly, according to the demand of local wood processing plants, the top five largest demand points are selected: Shengsheng, Hengxin, Xingyuan, Desheng and Zhanglong. Finally, four potential LCs are generated using GIS software while the following criteria were employed: (1) conforming to the government’s land-use plan; (2) having a large open field; and (3) proximity to main roads. The geographical locations of the nodes in the study region are showed in Fig. 3.

Fig. 3 Geographic location of a regional timber supply network in Fujian, China

Moreover, the forests designated for timber production in Jiangle County mainly consist of Masson’s pines, *Pinus massoniana* Lamb., and Chinese fir, *Cunninghamia lanceolata* (Lamb.) Hook. The total planting area of these two species is 53518.60 ha hm², accounting for 98.1% of the total timber forest area in the region. Based on their mature ages, the planning horizon is set to be 30 years, which is further divided into six time periods with five years in each period. The supply volume of each forest site is derived from the study by Fang (2017), in which the coming 30 years’ timber yields of this region were estimated based on a mathematical programming model with profit and carbon sink both being incorporated into the objective. Cost and emissions coefficients are based on Chen and Qiu (2017). The type code of the vehicles that departure from timber supply points and LCs are “SSF3091DHP77” (3,960 kg/6 m³) and “ZJ6SL43U045” (12,590 kg/19 m³) with diesel engines, respectively. The confidence level of demands is set to equal to 1. Information regarding the size of the
problem is given in Table 2.

Table 2 The size of the problem

To illustrate the effectiveness of NSGA-II, we compare its results with the exact results obtained by the normalized normal constraint method (NNC) (Messac et al. 2003) using Lingo 11.0 software. This method doesn’t need an initial weight for each objective and can yield a well-distributed set of all available Pareto solutions (Wang et al. 2011). The basic principle of the NNC method is to first decompose the bi-objective optimization into two single-objective optimization problems and obtain the values of the two objective functions, respectively. In this way, the extreme points of the Pareto solution set are obtained. Then a normalized increment to pursue other Pareto solutions is computed along the direction defined by the extreme points. To get enough Pareto solutions for mapping the Pareto frontier, the increment should be small enough. However, like other exact algorithms (e.g., e-constraints method), the principle of the NNC is to transform the multi-objective model into a single objective one, then solve it. In this regard, solving the transformed single objective model once can only obtain one Pareto solution at most, and it needs to solve the transformed single objective model many times to obtain enough Pareto solutions. Consequently, this approach extends the computation time, especially for large-scale problems. On the other hand, NSGA-II usually shows superiority in larger scale problems (Martínez-Salazar et al. 2014). Therefore, we only use the reduced versions of the problem (fewer time periods) to compare the performance of NSGA-II and an exact algorithm (the NNC). Fig. 4 presents the first Pareto frontier of the final generation of NSGA-II and the exact optimal Pareto frontier obtained by the NNC using Lingo
11.0, for problems with single time-period and 2 time-periods, respectively. NSGA-II is coded in MATLAB and all experiments are conducted on a computer with a 2-GB RAM, Intel i3 processor.

The solution sets obtained by NSGA-II are very close to the exact optimal frontiers and more evenly distributed. As expected, NSGA-II spend much less computation time than the exact algorithm. For example, the computation time for solving the 1-period and 2-period problems using NSGA-II are 7 s and 14 s respectively compared to 900 s and 25515 s using the exact algorithm (the NNC). Furthermore, when the number of time periods increases to three, Lingo could not solve even the single objective model within 24 hours.

The tradeoffs between carbon emissions and total cost are obvious with the optimal frontiers and the solutions with extreme values. Fig. 5 represents the first frontier obtained by NSGA-II for the 6-time-period case.

As shown in Fig.5, the tradeoff between total cost and the carbon emissions is nonhomogeneous at different part of the frontier curve. For example, at the left part of the figure, the reduction of emissions can be improved quickly by slightly increasing the total cost from 33 to 34 million $, and after that the potential of carbon emissions elimination is small and it causes significant increase in total cost to achieve even a
slight reduction. At the beginning, adjusting the timber flow in the supply network can reduce emissions through choosing roads with less emissions (e.g., roads with low rolling resistance and/or low gradient), which just needs a minor extra cost. However, to achieve further carbon emissions reduction, more facilities are necessary, which contributes a lot to the total cost.

To show the performance of the credibility-based fuzzy programming model in terms of its handling of demand uncertainty, numerical tests are carried out under different credibility confidences and the non-dominated solutions are derived (Fig.6).

Fig. 6 Non-dominated solutions under different credibility confidences

It is obvious that the non-dominated frontiers move to left and down when the minimum feasibility degree is decreased, because more timber should be transported to satisfy the demands and reduce the infeasibility risk at higher confidence levels. On the other hand, when the credibility confidence is low, the timber transportation volume is small. In this case, there is a much difference between the total supply and the total demand. Such a looser relationship between supply and demand helps effective transportation organization and provides more opportunities for reducing cost and carbon emissions.

5. Managerial implications

As LCs play an important role in sorting, consolidation, processing, and storage in the supply network, the mileage travelled by vehicles decreases as the amount of products transited by LCs or the number of LCs increases (Elhedhli and Merrick, 2012), and transportation cost and transportation-related GHG emissions decrease consequently.
However, opening and operating LCs contribute considerably to the total cost. Model solutions may select more LCs (Fig. 7) and/or allocate more timber to be transited through LCs to achieve lower carbon emissions (Fig. 7).

Fig. 7 Two solutions of a certain period with different location decisions

Fig. 7 shows two different solutions consisting of two different sets of LCs selected, with one having a lower total cost and the other having lower GHG emissions. The lower-cost solution (7.33$/m^3, 3.84 kg CO_2/m^3) includes only LC 2 [Fig. 7 (a)] while the lower-emissions solution (10.53$/m^3, 3.58 kg CO_2/m^3) consists of LCs 1, 2, and 4 [Fig. 7 (b)].

Fig. 8 shows two different solutions with the same number and locations of LCs but different timber flows along edges. In the solution with lower carbon emissions (8.45$/m^3, 3.61 kg CO_2/m^3) [Fig. 8 (b)], more timber is transited through LCs than in the solution with lower total cost (7.51$/m^3, 3.67 kg CO_2/m^3) [Fig. 8 (a)]. This implies that a shift in the priorities of objectives could lead to changes in both transportation routing and flows along the edges even with the same set of supply points, demand points, and LCs.

Table 3 displays the proportions of the plants’ demands served by LCs across all the time periods, which gives some geographical insights into supply network design. For the plant that is far away from supply sites such as Shengsheng, almost all of its demand is served by LC 2 in all time periods. In contrast, plants that are close to
supply points but far from open LCs, such as zhanglong and Desheng, receive timber directly from nearby suppliers prior to from LCs.

Table 3 Proportion of plants’ demand served by LCs

We are interested in how the loss rate of materials at LCs for plants ($\varphi_j$) influences non-dominated solutions, because it represents the processing degree at LCs and even the regional logistics service level to some extent. Value-added logistics services usually mean extra processing (e.g., barking and bucking) of materials, which reduce the transport volume of timber. For example, furniture plants could assemble well-processed materials or parts directly. Generally, deeper processing means higher timber weight loss.

For comparison, the same loss rate of timber transported to all plants at LCs from a given LC is assumed and we vary this value from 0 to 0.5 and obtain a series of non-dominated solutions (Fig. 9). For ease of comparison, Min-max normalization is done. It clearly shows that the solutions achieve smaller values of both objectives as the loss rate becomes bigger. That is to say, the timber supply network with a higher timber processing loss rate at LCs exhibits lower total cost and lower carbon emissions. This is because loss rate means the saving of timber transportation from LCs to plants. The higher the loss rate, the smaller the transportation volume. Consequently, the cost and the carbon emissions associated with transportation are both reduced. Of course, this reduction requires efficient transportation organization of the whole timber supply network, as well as a high level of logistics service. In fact, improvements on timber logistics service require lots of efforts by multiple participants involved and this series of non-dominated solutions can aid decision
makers in deciding on what to implement.

Fig. 9 Non-dominated solutions of different loss rates at LCs

We are also interested in the influences of changes in the supply volume in each time period on the non-dominated solutions. With the same total supply volume in the planning horizon, different changes in the supply volume in each time period are assumed: unchanged, fluctuation, increase, and decrease. Fig. 10 illustrates the non-dominated solutions corresponding to various changes in the supply volume in each time period.

Fig. 10 Non-dominated solutions of changes in timber supply during a planning horizon

As expected, when the supply volume is kept unchanged, the lowest values of total cost and carbon emissions are obtained. In this scenario, the optimal solutions for each time period are the same. In contrast, the total cost and GHG emissions are the highest when the supply volume fluctuated. Because in this case the optimal results in any time period are different from those in other time periods, and the optimal solution for the whole planning horizon might not be optimal for any single time period.

When the available supply volume increases, the results have lower carbon emissions and total costs because LCs are opened gradually as the volume increases without any unnecessary carbon emissions and extra cost. On the contrary, when the volume shows a downward trend, several LCs are opened in the first period and then
some of them might be closed in the subsequent time periods as the volume decreases, which leads to higher carbon emissions and total cost.

Noteworthy, in the left and up part of Fig.10, where solutions are with low total costs and high CO$_2$ emissions, the differences among solutions in different supply scenarios are very small. This is because high level of carbon emissions indicates that few LCs or even no LC are open. However, which LCs to open and the corresponding network configuration impact objectives largely.

The experiments to show the influence of truck types on the non-dominated solutions are conducted as well. Because of the limitations of roads in forest, we fix the capacity ($Q_1$) of vehicles that departure from forest sites and change the type of vehicles traveling between LCs and plants, the corresponding capacity ($Q_2$) is from 6 m$^3$ to 40 m$^3$. Except trucks with capacity of 6 m$^3$ and 19 m$^3$ whose type codes are stated above (section 4), other specific truck type codes related to the capacities used in the analysis are: STQ3L63L9Y6 (12 m$^3$), CA5429XXYP4K2L11T6 (30 m$^3$) and LZC9400 (40 m$^3$). Fig. 11 shows the non-dominated solutions with different size of truck types.

When homogeneous fleet is applied, the non-dominated solutions are located at the highest part of Fig. 11. As the frontier formed by those solutions is very flat, a slight mitigation on carbon emissions is at the cost of significant increase on total cost. Furthermore, the non-dominated frontier moves to left and bottom as “$Q_2$” increasing, which means that using trucks with bigger capacity to transport between LCs and plants is necessary for LCs to play better role in timber logistics systems.
However, when “$Q_2$” reaches 30 m$^3$ and 40 m$^3$, the gaps between the non-dominated frontiers are very narrow, especially at high level of total cost. This is because opening more LCs relate to solutions with high total cost. So, there are more links between LCs and plants. Consequently, the transportation volume on a single link becomes smaller, where vehicles with big capacities lose their advantages. For the same reason, the solutions with lowest carbon emissions in those two scenarios only choose 2 LCs rather than 3 LCs as in other scenarios.

6. Conclusion

We develop an optimization model for a regional timber supply network with several real-world characteristics, including multiple objectives, multiple time-periods and fuzzy demands. The most distinguishing feature of the model is that it simultaneously incorporates these characteristics plus two transportation patterns: direct (without LCs) and transit (with LCs) timber transportation. Although this approach increases modeling complexity, we employ an effective multi-objective algorithm, NSGA-II to solve it and demonstrate its applicability using a real-world regional timber supply network case. Our theoretical model is generic and can be applied to supply chain design and managements in other regions and in other fields besides forestry, which deal with decision making involving multiple objectives, multiple periods and uncertainty.

The case study, including computation/solution experiments show the differences between optimal network configurations under different decision preferences, and verifies that our model can serve as an effective tool for the optimization of a multi-objective, multi-period timber supply network with uncertainties. Moreover, sensitivity analysis for the case study confirms that properly
selecting LCs and allocating raw materials transited through LCs and keeping supply volume relatively stable without large fluctuations can lower both transportation costs and associated GHG emissions.

This study can be extended in several aspects. Instead of using fuzzy programming to deal with demand uncertainty, future studies can use more sophisticated methods, for example, hybrid methods. In addition, more operational practice can be incorporated, such as multiple truck types, multiple products, and backhaul transportation. Finally, other multi-objective solution methods may be employed to compare their effectiveness and efficiency in solving complex SCND models.

Appendix A. Lemma 1

Lemma 1 If \( \xi = (f_1, f_2, f_3) \) is a triangular fuzzy number, and \( f_1 \leq f_2 \leq f_3 \), for the given credibility level \( \alpha \) (0.5 \leq \alpha \leq 1), then:

\[ Cr\{\xi \geq r\} \geq \alpha \Leftrightarrow r \leq (2\alpha - 1)f_1 + 2(1-\alpha)f_2 \]  
(26)

\[ Cr\{\xi \leq r\} \geq \alpha \Leftrightarrow r \geq 2(1-\alpha)f_2 + (2\alpha - 1)f_3 \]  
(27)

Proof. For equation (26),  

1. Obviously, if \( r > f_2 \), then \( Cr\{\xi \geq r\} < 0.5 \); hence, when \( \alpha \geq 0.5 \), \( Cr\{\xi \geq r\} \geq \alpha \Rightarrow \frac{2f_2 - f_1 - r}{2(f_1 - f_2)} \geq \alpha \Rightarrow r \leq (2\alpha - 1)f_1 + 2(1-\alpha)f_2 ; \) 

2. If \( r \leq (2\alpha - 1)f_1 + 2(1-\alpha)f_2 \), Then \( \frac{2f_2 - f_1 - r}{2(f_1 - f_2)} \geq \alpha \Rightarrow Cr\{\xi \geq r\} \geq \alpha \). 

Therefore, equation (26) is proven, and equation (27) can be proved similarly.
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Table 1 Notations

<table>
<thead>
<tr>
<th>Sets</th>
<th>Description</th>
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<tbody>
<tr>
<td>$H$</td>
<td>Set of timber supply points in the forest zone</td>
</tr>
<tr>
<td>$K$</td>
<td>Set of potential locations of logistics centers (LCs)</td>
</tr>
<tr>
<td>$P$</td>
<td>Set of timber demand points</td>
</tr>
<tr>
<td>$T$</td>
<td>Set of periods in the planning horizon</td>
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<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{it}$</td>
<td>Additional supply at supply point $i$ in time period $t$ (m$^3$)</td>
</tr>
<tr>
<td>$\tilde{N}_j$</td>
<td>Fuzzy number of accumulated lower demand at demand point $j$ in period $t$ (m$^3$)</td>
</tr>
<tr>
<td>$\tilde{N}^+_j$</td>
<td>Fuzzy number of accumulated upper demand at demand point $j$ in period $t$ (m$^3$)</td>
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<tr>
<td>$c_{ijt}$</td>
<td>Cost of a trip from point $i$ to point $j$ in period $t$ ($/trip$)</td>
</tr>
<tr>
<td>$V_k$</td>
<td>Capacity of LC $k$ (m$^3$)</td>
</tr>
<tr>
<td>$FO_k$</td>
<td>Cost of opening LC $k$ in time period $t$ ($)</td>
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<tr>
<td>$FC_k$</td>
<td>Cost of closing LC $k$ in time period $t$ ($)</td>
</tr>
<tr>
<td>$F_k$</td>
<td>Maintaining cost of LC $k$ in period $t$ ($)</td>
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<tr>
<td>$m_j$</td>
<td>Unit processing cost of timber at point $j$ in time period $t$ ($)</td>
</tr>
<tr>
<td>$g_k$</td>
<td>Unit handling cost of timber in LC $k$ in time period $t$</td>
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<tr>
<td>$e_{it}$</td>
<td>CO$_2$ emissions of the path from point $i$ to point $j$ in time period $t$ (Mg CO$_2$/trip)</td>
</tr>
<tr>
<td>$E_j$</td>
<td>Unit CO$_2$ emissions of timber processing at point $j$ in period $t$ (Mg CO$_2$/m$^3$)</td>
</tr>
<tr>
<td>$Q_1$</td>
<td>Maximum capacity of trucks that departure from timber supply points in forest sites (m$^3$)</td>
</tr>
<tr>
<td>$Q_2$</td>
<td>Maximum capacity of trucks that departure from LCs (m$^3$)</td>
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<td>$\eta_i$</td>
<td>Unharvest loss rate of timber supply capacity for a period at supply point $i$</td>
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<tr>
<td>$\phi_j$</td>
<td>Loss rate of timber processing at LCs for plant $j$</td>
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<tr>
<td>$\gamma$</td>
<td>Loss rate of timber storage for a period at LCs</td>
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<td>$CTT_t$</td>
<td>Total transportation cost of the supply network in period $t$</td>
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<td>$CFL_t$</td>
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<td>Fixed and variable costs associated with LCs in period $t$</td>
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<td>$CVP_t$</td>
<td>Processing cost at LCs and plants in period $t$</td>
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<tr>
<th>Decision Variables</th>
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<td>$Z_{kt}$</td>
<td>A binary integer decision variable that is 1 if LC $k$ is open in time period $t$ and 0 otherwise</td>
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<tr>
<td>$x_{ijt}$</td>
<td>Timber flow from point $i$ to point $j$ in time period $t$ (m$^3$)</td>
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<tr>
<td>$w_{ijt}$</td>
<td>Number of trips from point $i$ to point $j$ in time period $t$</td>
</tr>
<tr>
<td>$r_{it}$</td>
<td>Timber volume stored at supply point $i$ at the end of time period $t$ ($t = 0$ indicates initial supply) (m$^3$)</td>
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Table 2 The size of the problem

<table>
<thead>
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<th>Description</th>
<th>Value</th>
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<td>Number of potential LCs</td>
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<td>Number of plants</td>
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<td>Number of time periods</td>
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<td>Total number of variables</td>
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<tr>
<td>Number of nonlinear variables</td>
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<tr>
<td>Number of integer variables</td>
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<tr>
<td>Number of constraints</td>
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<tr>
<td>Number of nonlinear constraints</td>
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Table 3 Proportion of plants’ demand served by LCs

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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<tbody>
<tr>
<td>Shengsheng</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.9953</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Henxing</td>
<td>0.5536</td>
<td>1</td>
<td>0.1280</td>
<td>0.9991</td>
<td>1</td>
<td>0.9997</td>
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<tr>
<td>Xingyuan</td>
<td>0.9995</td>
<td>0.4387</td>
<td>1</td>
<td>0</td>
<td>0.5788</td>
<td>0.3982</td>
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<td>Desheng</td>
<td>0</td>
<td>0</td>
<td>0.7484</td>
<td>0.7645</td>
<td>0.0180</td>
<td>0.7775</td>
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<tr>
<td>Zhanglong</td>
<td>0</td>
<td>0.4050</td>
<td>0.3938</td>
<td>0.9947</td>
<td>0</td>
<td>0.5533</td>
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