Fuzzy Programming Models for Minimax Location Problem

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Abstract: This paper discusses the minimax location problem with fuzzy locations of customers on a plane bounded by a convex polygon under a minimax criterion. Three types of fuzzy programming are presented for this problem according to different criteria, and Euclidean distances are assumed as the scenario. For solving the proposed models, a hybrid intelligent algorithm is designed.

Keywords: Minimax location problem, fuzzy programming, genetic algorithm

I. Introduction

Facility location problem (FLP) is a classical topic involving a large class of problems. For its broad application background, FLP is studied by many researchers. Minimax location problem (MLP) is a special type of FLP, which means locating new facilities under the minimax criteria.

Much work has been done on MLP, most of which is for deterministic case. That is, parameters of the problem are all deterministic. Some people considered MLP with Euclidean distances such as in Elzinga & Hearn [9][10] and Hearn & Vijay [12]. Besides Euclidean distances, some other people considered MLP with Rectangular distances on account of practical problems where the travelling paths are streets, corridors and so on. These work involves Morris [23], and Dearing & Francis [7]. In these literatures, deterministic MLPs have been investigated thoroughly, and many excellent results have been obtained by classical mathematical approaches.

In practice, some parameters are always given imprecisely. In other words, they are fuzzy. Then fuzzy set theory is needed. In the past decades, there are many people who have studied FLP by fuzzy logic approaches such as Bhattacharya \textit{et al.} [1][2], Canós \textit{et al.} [4], Chen and Wei [5], Darzentas [6], Rao and Saraswati [24]. Note that all the parameters in these problems are deterministic. Different from the above-mentioned papers, Zhou and Liu [27] investigated capacitated location-allocation problem and bi-criteria FLP with fuzzy demands of customers, and some fuzzy programming models are initiated for these problems.

In this paper, locations of customers are assumed to be fuzzy, and some fuzzy programming models are proposed for MLP under the minimax criterion. The paper is organized as follows. Notations are given in Section 2. An MLP with fuzzy locations of customers with Euclidean distances is formulated as fuzzy programming models in Section 3, involving fuzzy expected value model (EVM), fuzzy chance-constrained programming (CCP) and fuzzy dependent-chance programming (DCP). For solving these fuzzy models more efficiently, fuzzy simulation, neural network (NN) and genetic algorithm (GA) are integrated to produce a powerful hybrid intelligent algorithm in Section 4.

II. Minimax Location Problem

MLP is to locate emergency service facilities such as ambulance bases and fire stations. One of the important characteristics is the pressure of time. Therefore, it may be desirable to minimize the maximal distance from the facilities to any of customers serviced. Another is outbreak of events. Since accidents always happen occasionally and unanticipative, people cannot know the place that will need service. Thus locations of customers are fuzzy rather than deterministic.

Let \((x_i, y_i), i = 1, 2, \cdots, n\) be the locations of \(n\) facilities to be located. Here Euclidean distances are used as the measure scenario.

Obviously, each customer should be supplied by the nearest facility. We can describe a deterministic weighted minimax location problem as follows,

\[
\min_{x,y} \max_{1 \leq j \leq m} \min_{1 \leq i \leq n} \sqrt{(x_i - a_j)^2 + (y_i - b_j)^2} \quad (1)
\]

where \((a_j, b_j), j = 1, 2, \cdots, m\) are the fixed locations of...
customers, and
\[
(x, y) = \begin{pmatrix}
x_1 & y_1 \\
x_2 & y_2 \\
\vdots & \vdots \\
x_n & y_n
\end{pmatrix}.
\]

In addition, an assumption is given that facilities to
be located have some undesirable aspects such as dumping
sites for nuclear wastes so that facilities should be
at as far as possible from any customer. This is the so-
called maximin location problem, which is to maximize
the minimal distance between any customer and facility.
We may describe a maximin location problem as
\[
\max_{x, y} \min_{1 \leq i \leq m} \min_{1 \leq j \leq n} \sqrt{(x_i - a_j)^2 + (y_i - b_j)^2}. \tag{2}
\]
It is clear that
\[
\min_{1 \leq i \leq m} \min_{1 \leq j \leq n} \sqrt{(x_i - a_j)^2 + (y_i - b_j)^2} = \min_{1 \leq j \leq m} \min_{1 \leq i \leq n} \sqrt{(x_i - a_j)^2 + (y_i - b_j)^2}.
\]

Hence, a maximin location problem is often described as
\[
\max_{x, y} \min_{1 \leq j \leq m} \min_{1 \leq i \leq n} \sqrt{(x_i - a_j)^2 + (y_i - b_j)^2}. \tag{3}
\]

Note that from the optimal solution of (1) we may
estimate the shortest time for any customer to get cor-
responding services after accidents or demands happen,
which is the very important information in practice.

III. MLP Fuzzy Programming Models

Note that when the fixed locations \((a_j, b_j), j = 1, 2, \cdots, m\)
of customers are replaced by some fuzzy locations
\((\tilde{a}_j, \tilde{b}_j), j = 1, 2, \cdots, m\), (1) and (3) become meaningless.
In order to model this type of problems with fuzzy pa-
rameters, a theoretic framework of fuzzy programming
is suggested as an effective method. Much work has
been done on fuzzy programming models in the litera-
tures such as Liu and Liu [22], Liu and Iwamura [18][19],
Liu [20], and Liu [15]. In this section fuzzy programming
models will be initiated for MLP.

Before modeling the fuzzy MLP, let us give a no-
tation. Suppose that \(\tilde{a}_j, \tilde{b}_j\) are defined on a possibility
space \((\Theta, P(\Theta), \text{Pos})\), and denote realizations of \(\tilde{a}_j, \tilde{b}_j\) as
\(\tilde{a}_j(\theta), \tilde{b}_j(\theta), \theta \in \Theta\), for \(j = 1, 2, \cdots, m\), respectively.
It is clear that the maximum distance between any facility
and customer supplied can be estimated after the fuzzy
locations of customers are realized. That is, for each \(\theta \in \Theta\), there is a relative maximum distance
\[
L_{\max}(x, y | \theta) = \max_{1 \leq j \leq m} \min_{1 \leq i \leq n} \sqrt{(x_i - \tilde{a}_j(\theta))^2 + (y_i - \tilde{b}_j(\theta))^2}.
\]

Similarly, we denote the relative minimum distance be-
tween any facility and customer as
\[
L_{\min}(x, y | \theta) = \min_{1 \leq j \leq m} \min_{1 \leq i \leq n} \sqrt{(x_i - \tilde{a}_j(\theta))^2 + (y_i - \tilde{b}_j(\theta))^2}
\]
for each \(\theta \in \Theta\). Note that \(L_{\max}(x, y | \theta)\) and \(L_{\min}(x, y | \theta)\)
are both fuzzy variables.

3.1 Fuzzy Expected Value Model

In order to make unambiguous fuzzy programming mod-
els, Liu and Liu [22] presented a series of fuzzy EVM, in
which the underlying philosophy is based on selecting the
decision with minimum expected cost. Here, fuzzy EVM
will be provided for MLP under the minimax criterion.

As described in ([22]), we need only replace the fuzzy
distances \(L_{\max}(x, y | \theta)\) and \(L_{\min}(x, y | \theta)\) by their ex-
pected values. There are many ways to define a mean
value for fuzzy variables in the literatures such as Cam-
pos and Gonzalez [3], Dubois and Prade [8], Gonzalez
[11], Helifpern [13] and Yager [25][26]. Here we use the
definition of expected value operator by Liu and Liu [22]
as
\[
E[\xi] = \int_{0}^{+\infty} Cr\{\xi \geq r\}dr - \int_{-\infty}^{0} Cr\{\xi \leq r\}dr, \tag{4}
\]
where \(Cr\) is the credibility operator. Especially, if \(\xi\) is a
nonnegative fuzzy variable, then
\[
E[\xi] = \int_{0}^{+\infty} Cr\{\xi \geq r\}dr.
\]

Considering minimizing the expected value of the
maximum distance \(L_{\max}(x, y | \theta)\) with assumption that
the expected value of the minimum distance \(L_{\min}(x, y | \theta)\)
does not exceed a given level \(L\), we may have the follow-
ing fuzzy EVM for MLP,
\[
\begin{cases}
\min_{x, y} \int_{0}^{+\infty} Cr\{\theta \in \Theta \mid L_{\max}(x, y | \theta) \geq r\} \, dr \\
\text{subject to:} \\
\int_{0}^{+\infty} Cr\{\theta \in \Theta \mid L_{\min}(x, y | \theta) \geq r\} \, dr \leq L \\
C(x, y)^T D \leq D
\end{cases}
\tag{5}
\]
where \(C\) is a matrix of \(p \times 2\) dimension and \(D\) is a vector
of \(p\) dimension associated with a given convex polygon.
Model (5) shows locating new facilities optimally on a
plane bounded by a convex polygon from the mean value
view.
3.2 Fuzzy Chance-Constrained Programming

In Liu and Iwamura [18][19] and Liu [20], a spectrum of fuzzy chance-constrained programming (CCP) is presented, which provides means of allowing the decision-maker to consider objectives and constraints in terms of the possibility of their attainment. In this section, the theory will be used to formulate the fuzzy MLP.

We assume that the decision-maker assigns the following target levels and priority structure: At the first priority, the maximum distance between any facility and customers supplied should not exceed a given level \( \mathcal{L}_1 \) at least \( \alpha_1 \) of time, where \( \alpha_1 \) is the confidence level provided as an appropriate safety margin by the decision-maker. Fuzzy CCP involves maximax CCP and minmax CCP. On the one hand, the \( \alpha_1 \)-optimistic maximum distance (see [18][19]) is expected to be minimized. That is,

\[
\text{Pos} \left\{ \theta \in \Theta \mid L_{max}(x, y|\theta) - \mathcal{L}_1 \leq d_1^+ \right\} \geq \alpha_1, \quad (6)
\]

where \( d_1^+ \) is the \( \alpha_1 \)-optimistic positive deviation from \( \mathcal{L}_1 \), defined as

\[
\min \left\{ d \in \mathbb{R} \mid \text{Pos} \left\{ \theta \in \Theta \mid L_{max}(x, y|\theta) - \mathcal{L}_1 \leq d \right\} \geq \alpha_1 \right\}
\]

and \( d_1^+ \) is to be minimized.

At the second priority, the maximum distance between any facility and customers should not exceed a given level \( \mathcal{L}_2 \) at least \( \alpha_2 \) of time. Considering minimizing the \( \alpha_2 \)-optimistic minimum distance, we have

\[
\text{Pos} \left\{ \theta \in \Theta \mid \mathcal{L}_2 - L_{min}(x, y|\theta) \leq d_2^- \right\} \geq \alpha_2, \quad (7)
\]

where \( d_2^- \) is the \( \alpha_2 \)-optimistic negative deviation from \( \mathcal{L}_2 \), defined as

\[
\min \left\{ d \in \mathbb{R} \mid \text{Pos} \left\{ \theta \in \Theta \mid \mathcal{L}_2 - L_{min}(x, y|\theta) \leq d \right\} \geq \alpha_2 \right\}
\]

and \( d_2^- \) is to be minimized.

Combining (6) and (7), we may propose the fuzzy maximax chance-constrained goal programming for MLP with combined criteria as follows,

\[
\begin{align*}
\text{lemin} & \left\{ d_1^+, d_2^- \right\} \\
\text{subject to:} & \\
& \text{Pos} \left\{ \theta \in \Theta \mid L_{max}(x, y|\theta) - \mathcal{L}_1 \leq d_1^+ \right\} \geq \alpha_1 \\
& \text{Pos} \left\{ \theta \in \Theta \mid \mathcal{L}_2 - L_{min}(x, y|\theta) \leq d_2^- \right\} \geq \alpha_2 \\
& C(x, y)^T \leq D \\
& d_1^+, d_2^- \geq 0.
\end{align*}
\]

On the other hand, following the idea of fuzzy minmax CCP in [14], and considering minimizing the \( \beta_1 \)-pessimistic maximum distance and maximizing the \( \beta_2 \)-pessimistic minimum distance, the fuzzy MLP under both minmax criteria may be formulated as follows,

\[
\begin{align*}
\text{lemin} & \left\{ \max d_1^+ \lor 0, \max d_2^- \lor 0 \right\} \\
\text{subject to:} & \\
& \text{Pos} \left\{ \theta \in \Theta \mid L_{max}(x, y|\theta) - \mathcal{L}_1 \geq d_1^+ \right\} \geq \beta_1 \\
& \text{Pos} \left\{ \theta \in \Theta \mid \mathcal{L}_2 - L_{min}(x, y|\theta) \geq d_2^- \right\} \geq \beta_2 \\
& C(x, y)^T \leq D
\end{align*}
\]

where \( d_1^+ \lor 0 \) is called as the \( \beta_1 \)-pessimistic positive deviation from \( \mathcal{L}_1 \), defined as

\[
\max \left\{ d \lor 0 \mid \text{Pos} \left\{ \theta \in \Theta \mid L_{max}(x, y|\theta) - \mathcal{L}_1 \geq d \right\} \geq \beta_1 \right\}
\]

and \( d_2^- \lor 0 \) is called as the \( \beta_2 \)-pessimistic negative deviation from \( \mathcal{L}_2 \), defined as

\[
\max \left\{ d \lor 0 \mid \text{Pos} \left\{ \theta \in \Theta \mid \mathcal{L}_2 - L_{min}(x, y|\theta) \geq d \right\} \geq \beta_2 \right\}.
\]

3.3 Fuzzy Dependent-Chance Programming

Following the idea of DCP in stochastic environments, Liu [15] provided a series of fuzzy DCP models, in which the underlying philosophy is based on selecting the decision with maximum possibility to meet the event. The theory of fuzzy DCP will be used to model the fuzzy MLP here.

In practice, a concept of emergency limit is often referred to, which has strong application backgrounds. For example, Emergency Medical Service 1973 of American prescribed that emergency medical services to villages must arrive in thirty minutes, and to urban regions in ten minutes. In China, there are similar regulations on fire protection. In these cases people certainly want to maximize the possibility to arrive on time.

For one thing, we consider maximizing the possibility that the maximum distance does not exceed a given level \( \mathcal{L}_3 \). Secondly, it is supposed that the possibility that the maximum distance between any facility and customer is not under a given level \( \mathcal{L}_4 \) should be maximized. Thus, we have the following fuzzy dependent-chance multi-objective programming for MLP,

\[
\begin{align*}
\max & \text{Pos} \left\{ \theta \in \Theta \mid L_{max}(x, y|\theta) \leq \mathcal{L}_3 \right\} \\
\max & \text{Pos} \left\{ \theta \in \Theta \mid L_{min}(x, y|\theta) \geq \mathcal{L}_4 \right\} \\
\text{subject to:} & \\
& C(x, y)^T \leq D,
\end{align*}
\]

where \( \mathcal{L}_3 \) is the predetermined emergency limit and \( \mathcal{L}_4 \) is the predetermined level of the maximum distance.

IV. Solution Procedure

In this section, in order to solve fuzzy models (5)(8)(9)(10) effectively, a hybrid intelligent algorithm is designed.
4.1 Fuzzy Simulation

Fuzzy simulation is an efficient method of performing sampling experiments on the models of fuzzy systems, which is initiated by Liu [16][17], Liu and Iwamura [18][19][20]. Following their idea, a fuzzy simulation is suggested as follows,

**Step 1.** Set \( E = 0 \).

**Step 2.** Randomly generate \( u_{j1}, u_{j2}, \ldots, u_{jM} \) and \( v_{j1}, v_{j2}, \ldots, v_{jM} \) from the \( \varepsilon \)-level sets of \( \tilde{a}_j \) and \( \tilde{b}_j \) for \( j = 1, 2, \ldots, m \) respectively, where \( \varepsilon \) is a sufficiently small number, and \( M \) is a large enough number.

**Step 3.** Set \( a = l_1 \land l_2 \land \cdots \land l_M, b = l_1 \lor l_2 \lor \cdots \lor l_M \), and \( \mu_k = \mu_{\tilde{a}_k} \left( u_{1k} \right) \land \cdots \land \mu_{\tilde{a}_m} \left( u_{mk} \right) \land \mu_{\tilde{b}_1} \left( v_{1k} \right) \land \cdots \land \mu_{\tilde{b}_m} \left( v_{mk} \right) \), where \( l_k = \max_{1 \leq j \leq M, 1 \leq i \leq n} \min \left\{ \left( x_i - u_{jk} \right)^2 + \left( y_i - v_{jk} \right)^2, k = 1, 2, \ldots, M \right\} \), respectively.

**Step 4.** Randomly generate \( r \in [a, b] \).

**Step 5.**

\[
E \leftarrow E + \frac{1}{2} \max_{k=1,2,\ldots,M} \{ \mu_k \mid l_k \geq r \} + \frac{1}{2} - \frac{1}{2} \max_{k=1,2,\ldots,M} \{ \mu_k \mid l_k < r \}.
\]

**Step 6.** Repeat the fourth and fifth steps for \( N \) times.

**Step 7.** Return \( a + E \cdot \left( b - a \right)/N \).

Certainly, we can design a similar fuzzy simulation process for computing

\[
\int_0^{+\infty} \text{Cr} \left\{ \theta \in \Theta \mid L_{\min} (x, y|\theta) \geq r \right\} dr.
\]

In order to estimate

\[
L = \min \left\{ d \mid \text{Pos} \left\{ \theta \in \Theta \mid L_{\min} (x, y|\theta) - \mathcal{L}_1 \leq d \right\} \geq \alpha_1 \right\}
\]

where \( d \geq 0 \), we design a fuzzy simulation as follows,

**Step 1.** Set \( L = +\infty \).

**Step 2.** Randomly generate \( u_j \) and \( v_j \) from the \( \alpha \)-level sets of \( \tilde{a}_j \) and \( \tilde{b}_j \), \( j = 1, 2, \ldots, m \) respectively.

**Step 3.** Compute

\[
temp = \max_{1 \leq j \leq m} \min_{1 \leq i \leq n} \sqrt{(x_i - u_j)^2 + (y_i - v_j)^2}.
\]

If \( L > temp \), then we set \( L = temp \).

**Step 4.** Repeat the second and third steps \( N \) times.

**Step 5.** Return \( L - \mathcal{L}_1 \lor \theta \).

Some similar fuzzy simulations are also designed for

\[
\begin{align*}
\min \left\{ d \mid \text{Pos} \left\{ \theta \in \Theta \mid \mathcal{L}_2 - L_{\min} (x, y|\theta) \leq d \right\} \geq \alpha_2 \right\}, \\
\max \left\{ d \mid \text{Pos} \left\{ \theta \in \Theta \mid L_{\max} (x, y|\theta) - \mathcal{L}_1 \geq d \right\} \geq \beta_1 \right\}, \\
\max \left\{ d \mid \text{Pos} \left\{ \theta \in \Theta \mid \mathcal{L}_2 - L_{\min} (x, y|\theta) \geq d \right\} \geq \beta_2 \right\}.
\end{align*}
\]

In addition, in order to estimate the possibility

\[
T = \text{Pos} \left\{ \theta \in \Theta \mid L_{\max} (x, y|\theta) \leq \mathcal{L}_3 \right\},
\]

a fuzzy simulation is suggested as follows,

**Step 1.** Set \( T = \alpha \), where \( \alpha \) is a lower estimation of the possibility \( T \).

**Step 2.** Randomly generate \( u_j \) and \( v_j \) from the \( \alpha \)-level sets of \( \tilde{a}_j \) and \( \tilde{b}_j \), \( j = 1, 2, \ldots, m \) respectively.

**Step 3.** Set \( \mu = \mu_{\tilde{a}_1} (u_1) \land \cdots \land \mu_{\tilde{a}_m} (u_m) \land \mu_{\tilde{b}_1} (v_1) \land \cdots \land \mu_{\tilde{b}_m} (v_m) \).

**Step 4.** If \( \max_{1 \leq j \leq m, 1 \leq i \leq n} \sqrt{(x_i - u_j)^2 + (y_i - v_j)^2} \leq \mathcal{L}_3 \) and \( T < \mu \), then we set \( T = \mu \).

**Step 5.** Repeat the second to fourth steps for \( N \) times.

**Step 7.** Return \( T \).

Following the idea, we may also design a similar fuzzy simulation process to get

\[
\text{Pos} \left\{ \theta \in \Theta \mid L_{\min} (x, y|\theta) \geq \mathcal{L}_4 \right\}.
\]

4.2 Hybrid Intelligent Algorithm

Although fuzzy simulations designed above are able to compute the uncertain functions like

\[
\begin{align*}
U_1 : (x, y) & \rightarrow \int_0^{+\infty} \text{Cr} \left\{ \theta \in \Theta \mid L_{\max} (x, y|\theta) \geq r \right\} dr, \\
U_2 : (x, y) & \rightarrow \int_0^{+\infty} \text{Cr} \left\{ \theta \in \Theta \mid L_{\min} (x, y|\theta) \geq r \right\} dr, \\
U_3 : (x, y) & \rightarrow \text{Pos} \left\{ \theta \in \Theta \mid L_{\max} (x, y|\theta) \leq \mathcal{L}_3 \right\},
\end{align*}
\]

it is a time-consuming process indeed. In order to speed up the solution process, NNs are employed to approximate there uncertain functions, which can also compensate for the error of training data obtained by fuzzy simulations.

For solving those fuzzy models in Section 3 efficiently, fuzzy simulation, NNs and GA are integrated to produce a hybrid intelligent algorithm. We describe the solution process for model (5) as follows,
Step 1. Generate training input-output data for uncertain function $U_1$ and $U_2$ by fuzzy simulation.

Step 2. Train a neural network to approximate $U_1$ and $U_2$ according to the generated training data.

Step 3. Initialize $\text{pop}\_\text{size}$ chromosomes $V_l = (x^l, y^l)$, $l = 1, 2, \ldots, \text{pop}\_\text{size}$ from the potential region $\{C(x, y)^T \leq D\}$ uniformly.

Step 4. Calculate the objective values

\[
\int_0^{+\infty} Cr\{\theta \in \Theta \mid L_{\max}(x^l, y^l|\theta) \geq r\} \, dr
\]

for all chromosomes $V_l$, $l = 1, 2, \ldots, \text{pop}\_\text{size}$ respectively, by the trained NN.

Step 5. Compute the fitness of $V_l$ for $l = 1, 2, \ldots, \text{pop}\_\text{size}$ respectively, according to the objective values.

Step 6. Select the chromosomes by spinning the roulette wheel.

Step 7. Update $V_l$, $l = 1, 2, \ldots, \text{pop}\_\text{size}$ by crossover and mutation operations, where the feasibility of chromosomes may be checked by $\{C(x^l, y^l)^T \leq D\}$ and

\[
\int_0^{+\infty} Cr\{\theta \in \Theta \mid L_{\min}(x^l, y^l|\theta) \geq r\} \, dr \leq T,
\]

which can be obtained by the trained NN.

Step 8. Repeat the fourth to seventh steps for a given number of cycles.

Step 9. Report the best chromosome $V^* = (x^*, y^*)$ as the optimal locations.

Since the two objectives are conflict in model (10), there is no optimal solution that simultaneously optimizes both objective functions. Then a compromise model is suggested whose solution is called a compromise solution. There are many compromise models presented in the literatures. Here we adopt the idea of weighting the objective functions, and then translate model (10) into the following model,

\[
\begin{aligned}
\max_{x, y} & \quad \lambda_1 \text{Pos}\{\theta \in \Theta \mid L_{\max}(x, y|\theta) \leq T_3\} \\
& \quad + \lambda_2 \text{Pos}\{\theta \in \Theta \mid L_{\min}(x, y|\theta) \geq T_4\} \\
\text{subject to:} & \quad C(x, y)^T \leq D,
\end{aligned}
\]

where $\lambda_1, \lambda_2$ are weights proposed by the decision maker. Therefore, we can design another hybrid intelligent algorithm by computing the objective function

\[
\begin{aligned}
\lambda_1 \text{Pos}\{\theta \in \Theta \mid L_{\max}(x, y|\theta) \leq T_3\} \\
& \quad + \lambda_2 \text{Pos}\{\theta \in \Theta \mid L_{\min}(x, y|\theta) \geq T_4\}
\end{aligned}
\]

instead in Step 4.

V. Conclusion

Minimax location problem on a plane bounded by a convex polygon is formulated as fuzzy programming models including the expected value model, chance-constrained goal programming model, and dependent-chance multiobjective programming model, where locations of customers are supposed to be fuzzy variables and Euclidean distances are assumed as the scenario. For solving the proposed models efficiently, all kinds of fuzzy simulations are designed for uncertain functions and embedded into neural network and genetic algorithm to produce a hybrid intelligent algorithm.

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References


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