Transportation Infrastructure Precast Innovation Center (TRANS-IPIC)

University Transportation Center (UTC)

Optimizing Maintenance Decisions for Precast Concrete Bridges

UI-25-RP-04

Quarterly Progress Report

For the performance period ending 9/30/2026

Submitted by:

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Collaborators / Partners:

None

Submitted to:

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Project Description:

1. Research Plan - Statement of Problem

The American Society of Civil Engineers (ASCE) reports that approximately 56% of the nation's 623,000 bridges are in fair or poor condition that caused substantial safety risks and traffic delays for millions of daily users. This has been caused by the lack of funding for the rehabilitation and reconstruction of aging bridges which created a $191.3 billion rehabilitation backlog and a $373 billion funding gap over the next decade (ASCE, 2025; FHWA, 2025). To address this pressing challenge, federal and state departments of transportation (DOTs) need to optimize the use of limited funding and budgets for the rehabilitation of aging bridges to maximize their overall performance and durability. This presents federal and state DOTs with several challenges, including how to (1) optimize maintenance and repair decisions for precast concrete bridges; (2) maximize durability of precast concrete bridges; (3) minimize bridge maintenance costs; and (4) generate and analyze trade-offs among these bridge optimization objectives. To address these challenges, this research will develop robust multi-objective models and a user-friendly decision support tool for optimizing maintenance decisions for precast concrete bridges. This perfectly aligns with the TRANS/IPIC mission of “providing gains in durability, safety, and economy as well as reducing environmental impact and resources required for repair and replacement” (TRANS-IPIC, 2025).

2. Research Plan - Summary of Project Activities (Tasks)

Task 1: Identify all relevant decision variables representing maintenance actions for precast concrete bridge components throughout the user-specified planning horizon.

Task 2: Formulate objective functions to quantify the impact of the identified maintenance decision variables on critical optimization objectives, including extending bridge durability by maximizing its condition rating and minimizing bridge maintenance costs.

Task 3: Model all practical constraints that affect this multi-objective optimization problem to fully represent all limitations confronting state DOTs such as annual budgetary restrictions and bridge performance requirements.

Task 4: Implement the formulated model using various optimization techniques, including Mixed-Integer Programming (MIP), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO).

Task 5: Evaluate the computational efficiency and effectiveness of the implemented models using case studies of varying sizes and maintenance funding levels to illustrate their capabilities in prioritizing and optimizing maintenance and repair decisions for precast concrete bridges.

Task 6: Develop a practical decision support tool (DST) that integrates the developed models and friendly graphical user interface (GUI) to facilitate the use and adoption of the research development by State DOTs and bridge planners.

Project Progress:

3. Progress for each research task

Task 1 Progress: [100% completed]. Last quarter, the research team completed the first research task that focused on Identifying all relevant decision variables representing maintenance actions for each precast concrete bridge component throughout the user-specified planning horizon. For example, a binary decision variable ($X_{b,i,j,r}$) was defined to represent the selection of maintenance action j for each component i of bridge b during time period r of the planning horizon (Betz et al. 2024). These decisions can be represented by selections from a set of alternative maintenance actions such as no action, preventive maintenance, minor repair, rehabilitation, or replacement/major reconstruction.

Task 2 Progress: [100% completed]. Last quarter, the research team completed the second research task, which focused on formulating objective functions that quantify the effects of the identified maintenance decision variables on two key optimization objectives: maximizing bridge durability and minimizing total maintenance cost. The condition of each bridge component, including the deck,

superstructure, and substructure, is represented using the FHWA condition-rating scale from 0 to 9 (AASHTO 2025; FHWA 2025). The durability objective function maximizes the average component-weighted end-of-year condition rating across all bridges and planning years. The average condition rating is calculated by dividing the cumulative weighted end-of-year condition ratings by the total number of bridge-years, as shown in Eq. (1). For each component, the end-of-year condition rating is determined by adding the improvement associated with the selected maintenance action to the pre-maintenance condition rating, limiting the resulting rating to a maximum of 9, and applying the applicable deterioration associated with consecutive no-action decisions, as defined in Eq. (2). Similarly, the maintenance cost objective function is formulated to minimize the total cost of selected maintenance actions by summing the costs of selected actions across all bridges, components, and time periods, as shown in Eq. (3).

$$Max\ Average\ Bridge\ Component\ Condition\ Rating = Max \sum_{\mathrm{b}=1}^{B}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} \frac{\left(CR_{b,i,j,r}^{end} \ * \ W_i \ * \ X_{b,i,j,r}\right)}{B * R} \quad (1)$$

$$CR_{b,i,j,r}^{end} = min\left(CR_{b,\,i,r}^{pre} + \Delta\, CR_{b,i,j,r},\ 9\right) - Dr_{b,i,r} \quad (2)$$

$$Min\ Total\ Maintenance\ Costs = Min \sum_{\mathrm{b}=1}^{B}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R}\left(MC_{b,i,j,r} \ * \ X_{b,i,j,r}\right) \quad (3)$$

Where $CR_{b,i,j,r}^{end}$ represents the end-of-year condition rating of component i of bridge b, resulting from maintenance decision j in time period r and the associated deterioration effect, W_i represents the importance weight of component i with the component weights summing to 1 for each bridge, B represents the total number of bridges included in the case study, R represents the total number of years in the planning horizon, $CR_{b,\,i,r}^{pre}$ represents the condition rating of component i of bridge b before applying any maintenance decision in year r , $\Delta\, CR_{b,i,j,r}$ represents the improvement in the condition rating of component i of bridge b due to the selection of maintenance decision j in time period r. $Dr_{b,i,r}$ represents the deterioration effect of component i of bridge b in time period r based on consecutive no-action decisions, and $MC_{b,\,i,\,j,\,r}$ represents the maintenance cost of component i of bridge b due to the selection of maintenance decision j in time period r.

Task 3 Progress: [100% completed]. last quarter, the research team completed the third research task that focused on modeling all practical constraints that affect this multi-objective optimization problem to fully represent the limitations confronting state DOTs such as annual budgetary restrictions and bridge performance requirements. These constraints ensure that the optimization model generates only feasible and implementable maintenance solutions within the specified budget. For example, only one maintenance decision j can be selected for each component i of bridge b in any year r, as shown in Eq. (4). Similarly, the total maintenance cost for all components $(i = 1\ to\ I)$ of all bridges $(b = 1\ to\ B)$ in year r must be less than or equal to the maximum budget available in this year $Budget_r$, as shown in Eq. (5). Furthermore, each bridge component must satisfy the minimum acceptable condition-rating requirement to ensure acceptable service levels, as shown in Eq. (6).

$$\sum_{j=1}^{J} X_{b,i,j,r} = 1 \qquad \forall\, b,i,r \quad (4)$$

$$\sum_{b=1}^{B}\sum_{i=1}^{I}\sum_{j=1}^{J} MC_{b,i,j,r}\, X_{b,i,j,r} \ \leq \ Budget_r \ \ \forall\, r \in \{1,2,\dots R\} \quad (5)$$

$$CR_{b,\,i,j,r}^{end} \ \geq CR_i^{th} \qquad \forall b,i,r \quad (6)$$

Where $Budget_r$ represents the total available maintenance budget in year r, CR_i^{th} represents the minimum acceptable condition-rating threshold for component i

Task 4 Progress: [100% completed]. During this quarter, the research team completed the fourth research task, which focuses on implementing the formulated maintenance optimization model using various optimization techniques. To accomplish this, the research team developed six machine learning (ML) models to predict the initial condition ratings of bridge decks, using National Bridge Inventory (NBI)

data. These predicted condition ratings provide the baseline conditions required for evaluating the impacts of alternative maintenance decisions on bridge durability. The findings from the development of these ML models were summarized in a peer-reviewed manuscript that was accepted for publication in the ASCE Journal of Construction Engineering and Management on June 25, 2026.

The research team implemented the developed maintenance optimization formulation using three different optimization techniques: Mixed-Integer Programming (MIP), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). The three models were developed to solve the same multi-objective bridge maintenance planning problem by minimizing total maintenance costs while maximizing bridge-component condition ratings over the planning horizon. Each model incorporated the developed practical constraints, including annual budget limitations and minimum condition-rating requirements.

First, the MIP model provides an exact mathematical optimization approach that represents maintenance decisions using discrete decision variables and can identify globally optimal solutions while satisfying all modeled constraints. The model was used to identify the minimum-cost and maximum-durability endpoint solutions and generate intermediate Pareto solutions representing different tradeoffs between the two objectives (Betz et al. 2024). Second, the GA model provides a population-based metaheuristic optimization technique that iteratively improves candidate solutions using genetic operators such as selection, crossover, and mutation. In this study, the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a multi-objective extension of GA, was implemented to simultaneously minimize maintenance costs and maximize bridge-component condition ratings. NSGA-II ranks candidate solutions based on non-dominance and uses a crowding-distance mechanism to maintain solution diversity along the Pareto front, enabling the model to generate a broad range of cost-durability tradeoffs without explicitly evaluating the entire solution space (Helaly et al. 2026; Al-Ghzawi and El-Rayes 2024). Third, the PSO model provides a population-based metaheuristic optimization approach inspired by the collective movement of bird flocks and fish schools. The model iteratively updates the positions of candidate solutions, referred to as particles, based on each particle's best-known position and the best-known position identified by the swarm, thereby guiding the search toward promising combinations of maintenance decisions (Pan et al. 2018).

Task 5 Progress: [80% completed]. During this quarter, the research team started working on the fifth task, which focuses on evaluating the computational efficiency and effectiveness of the implemented models using a case study to illustrate their capabilities in prioritizing and optimizing maintenance and repair decisions for concrete bridges. The case study was selected in Champaign County and includes 49 $(B = 49)$ bridges represented by 147 components $(I = 147)$ from the National Bridge Inventory (NBI). Initial condition ratings range from 4 to 9. Alternative maintenance actions that can be selected by the optimization models $(J = 5)$ are no action, preventive maintenance, minor repair, rehabilitation, and replacement, and the planning horizon of this optimization decision making problem is assumed to be five years $(R = 5)$. The annual budget is $1.1 million, and each component must end every year with a condition rating of 5 or higher. The model also limits each bridge to one major action per year and each component to one major action over the planning horizon.

First, the MIP model was evaluated using an epsilon-constraint analysis that generated seven cost-durability alternatives, with a 180-second time limit applied to each primary and tie-break solve. The full analysis required 36.28 minutes. The certified minimum-cost solution resulted in a five-year maintenance cost of $1.068 million and an average condition rating of 6.51. Increasing the allowable cumulative cost raised the average condition rating to 8.07 at $5.409 million. All seven maintenance schedules passed the independent feasibility checks. However, only the minimum-cost endpoint was certified as optimal, while the remaining six alternatives represent feasible best-found solutions because their respective optimization runs reached the specified time limit, as shown in Figure 1 and Table 1.

Table 1. Comparison of the developed optimization models.

Model	Runtime (min)	Reported Nondominated Alternatives	Lowest Cost Result	Highest Durability/Average Condition Rating
MIP	36.28	7	$1.068 M, Avg. condition 6.51	8.07, Cost $5.409 M
NSGA II	46.83	200	$1.190 M, Avg. condition 6.63	7.93, Cost $5.286 M
PSO	19.59	76	$1.668 M, Avg. condition 6.82	7.70, Cost $5.231 M

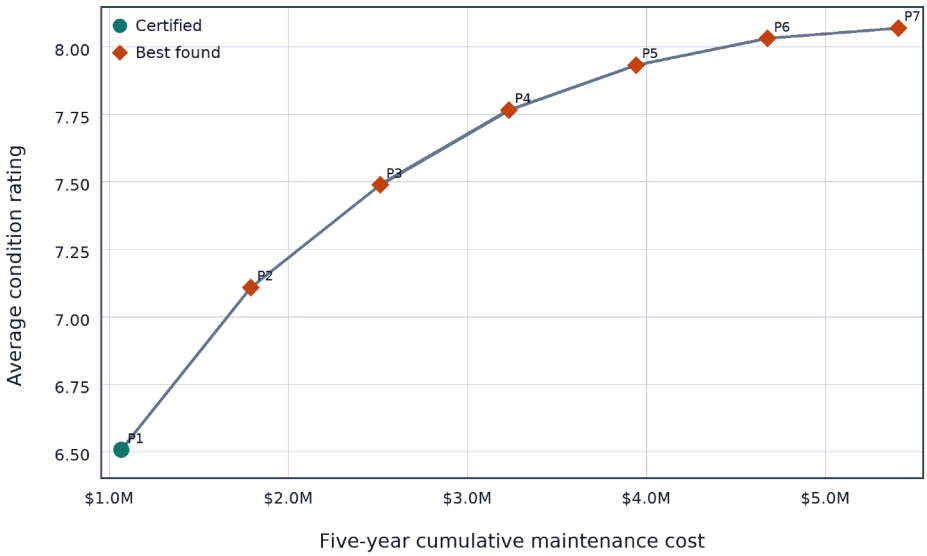


Figure 1. Pareto front generated using the MIP optimization model.

Second, the selected NSGA-II run used a population of 200, 1,000 generations, a crossover probability of 0.60, a mutation probability of 1/735, and random seed 42. The run required 46.83 minutes and produced 200 nondominated sets of maintenance decisions for all bridge components. The reported pareto front extends from a lowest-cost solution of $1.190 million with an average condition rating of 6.63 to a highest-average-condition solution of 7.93 with a cost of $5.286 million. The dense frontier provides a broad set of intermediate cost-durability tradeoffs, as shown in Figure 2 and Table 1.

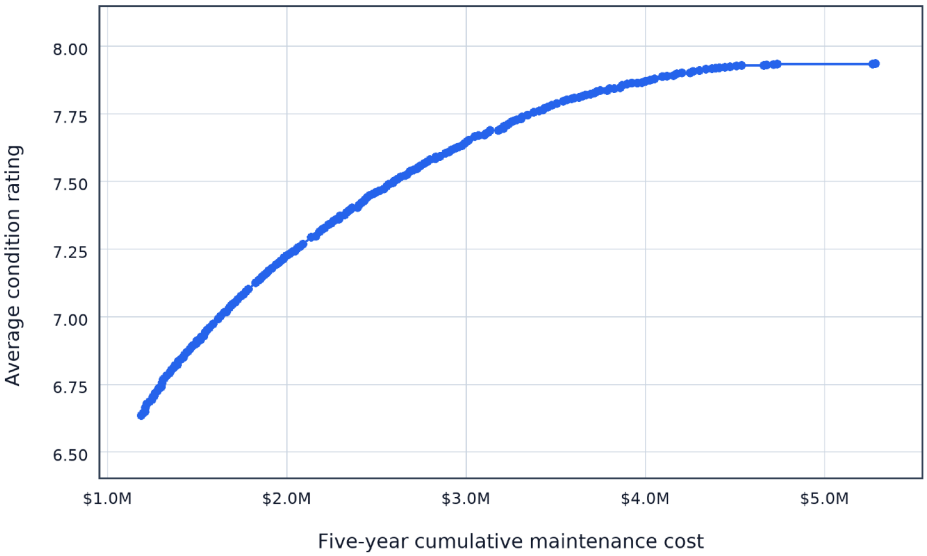


Figure 2. Pareto front generated using the NSGA-II optimization model.

Third, the selected PSO run used 200 particles, 1,000 iterations, an archive capacity of 200, inertia decreasing from 0.90 to 0.40, cognitive and social coefficients of 1.50, a velocity limit of 2, an effective mutation probability of 1/735, and random seed 42. A 50-iteration lookback and tolerance of 1e-6 were specified for early stopping. The run required 19.59 minutes and returned 76 feasible nondominated sets of maintenance decisions for all bridge components. The frontier ranges from a lowest-cost solution of $1.668 million with an average condition rating of 6.82 to an average condition rating of 7.70 at $5.231 million. PSO therefore completed the matched full run faster than MIP and NSGA-II, although its reported

frontier did not extend as far toward the low-cost or high-durability endpoints, as shown in Figure 3 and Table 1.

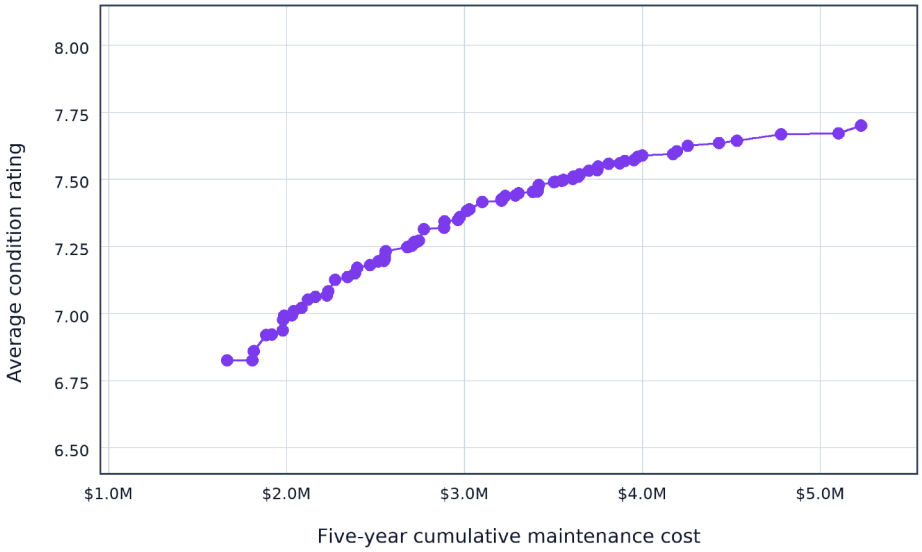


Figure 3. Pareto front generated using the PSO optimization model

Task 6 Progress: [0% completed] (Not Started).

4. Percent of research project completed

80% of total project completed through the end of this quarter.

5. Expected progress for next quarter

In the next quarter, the research team will finalize the fifth task by further evaluating the computational efficiency and effectiveness of the developed optimization models. This evaluation will include testing additional model parameter settings and comparing the MIP, NSGA-II, and PSO models based on solution quality, feasibility of generated maintenance schedules, and their ability to generate cost-durability tradeoffs along the Pareto front. Additionally, the research team will work on the final task, which focuses on developing a practical decision support tool (DST) that integrates the developed optimization models with a user-friendly graphical user interface (GUI) to facilitate the use and adoption of the research outcomes by State DOTs and bridge planners.

6. Educational outreach and workforce development

This quarter, the educational and workforce development (EWD) activities focused on enhancing the analytical and research skills of a female PhD student serving as the lead research assistant on this project. Her work involved collecting and analyzing bridge data from multiple databases and developing multi-objective optimization models. Additionally, the research team participated in all TRANS-IPIC monthly online webinars.

7. Technology Transfer

The research team developed six novel machine learning (ML) models to predict the condition ratings of concrete bridge decks using the National Bridge Inventory (NBI) database, the largest bridge inventory database in the United States. Additionally, the team developed three novel multi-objective optimization models using Mixed-Integer Programming (MIP), Non-dominated Sorting Genetic Algorithm II (NSGA-II), and Particle Swarm Optimization (PSO) to optimize maintenance decisions for concrete bridges. The research team will also develop a user-friendly decision support tool (DST) that integrates the developed models to facilitate their practical use by state DOTs and bridge planners.

Research Contribution:

8. Papers that include TRANS-IPIC UTC in the acknowledgments section:

The research team submitted a manuscript titled "*Machine Learning Models for Predicting Condition Rating of Cast-In-Place and Precast Concrete Bridge Decks*" to the *ASCE Journal of Construction Engineering and Management*, where it was accepted for publication on June 25, 2026. Additionally, the team submitted a manuscript to TRANS-IPIC for publication in the proceedings of the 2026 TRANS-IPIC Workshop, as follows:

- Helaly, H., K. El-Rayes, and E. J. Ignacio. 2026a. "*Machine Learning Models for Predicting Condition Rating of Cast-In-Place and Precast Concrete Bridge Decks"*. In press, *ASCE Journal of Construction Engineering and Management*.
- Helaly, H., K. El-Rayes, and E. J. Ignacio. 2026b. "Predicting Condition Rating of Concrete Bridge Decks." In *Proceedings of the 2026 TRANS-IPIC UTC Workshop*.

9. Presentations and Posters of TRANS-IPIC funded research:

The research team presented the preliminary findings of this research project at the 2026 Annual TRANS-IPIC UTC Workshop on April 14, 2026.

- El-Rayes, K., E. J. Ignacio, and H. Helaly. 2026. "Optimizing the Planning of Precast Concrete Bridges." Poster presentation at the 2026 TRANS-IPIC UTC Workshop.

10. Please list any other events or activities that highlights the work of TRANS-IPIC occurring at your university (please include any pictures or figures you may have). Similarly, please list any references to TRANS-IPIC in the news or interviews from your research.

None.

Appendix 1: Research Activities, leadership, and awards (cumulative, since the start of the project)

A. Number of presentations at academic and industry conferences and workshops of UTC findings
   - No. = 1: One poster presentation at the 2026 TRANS-IPIC Workshop held on April 14, 2026, in Rosemont, IL.

B. Number of peer-reviewed publications submitted based on outcomes of UTC funded projects
   - No. = 1: One manuscript was submitted to the *ASCE Journal of Construction Engineering and Management* in March 2026 and was accepted for publication on June 25, 2026.

C. Number of peer-reviewed journal articles published by faculty.
   - No. = One manuscript was published at the ASCE *Journal of Construction Engineering and Management* in May 2026 based on outcomes of UTC funded projects.

D. Number of peer-reviewed conference papers published by faculty.
   - No. = One manuscript was submitted to TRANS-IPIC for publication in the proceedings of the 2026 TRANS-IPIC Workshop.

E. Number of TRANS-IPIC sponsored thesis or dissertations at the MS and PhD levels.
   - No. MS thesis = 0
   - No. PhD dissertations = One ongoing PhD dissertation by Hadil Helaly
   - No. citations of each of the above =0

F. Number of research tools (lab equipment, models, software, test processes, etc.) developed as part of TRANS-IPIC sponsored research
   - Research Tool #1: Six novel machine learning (ML) models were developed to predict the condition rating of concrete bridge decks using the National Bridge Inventory (NBI) database.
   - Research Tool #2: Three novel multi-objective optimization models for planning maintenance decisions of precast concrete bridges (ongoing).
   - Research Tool #3: A user-friendly graphical user interface (GUI) designed to facilitate the use and adoption of the developed optimization models by State Departments of Transportation (DOTs) and bridge planners (ongoing).

G. Number of transportation-related professional and service organization committees that TRANS-IPIC faculty researchers participate in or lead.
   - Professional societies
     - No. participated in = 0
     - No. lead = 0
   - Advisory committees (No. participated in & No. led)
     - No. participated in = 0
     - No. lead = 0
   - Conference Organizing Committees (No. participated in & No. led)
     - No. participated in = 0
     - No. lead = 0
   - Editorial board of journals (No. participated in & No. led)
     - No. participated in = 0
     - No. lead = 0
   - TRB committees (No. participated in & No. led)
     - No. participated in = 0
     - No. lead = 0

H. Number of relevant awards received during the grant year
   - No. awards received = One award was received by Hadil Helaly (lead research assistant) — the 2025 TRANS-IPIC Outstanding Student of the Year, recognized at the Council of University Transportation Centers (CUTC) Awards Banquet during TRB 2026.

I. Number of transportation related classes developed or modified as a result of TRANS-IPIC funding.
   - No. Undergraduate = 2
   - No. Graduate = 2

J. Number of internships and full-time positions secured in the industry and government during the grant year.
   - No. of internships = 0
   - No. of full-time positions = 0

References:

AASHTO Manual for Bridge Evaluation (MBE). 2025. *Bridge Design Manual*.

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Al-Ghzawi, M., and K. El-Rayes. 2024. "Machine learning and multi-objective optimization methodology for planning construction phases of airport expansion projects." Journal of Air Transport Management, 115, 102550. https://doi.org/10.1016/j.jairtraman.2024.102550.

Betz, T., K. El-Rayes, and M. Grussing. 2024. "Multiyear Facility Maintenance Optimization." *Journal of Performance of Constructed Facilities*, 38 (2). American Society of Civil Engineers (ASCE). https://doi.org/10.1061/jpcfev.cfeng-4678.

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Pan, A., L. Wang, W. Guo, and Q. Wu. 2018. "A diversity enhanced multiobjective particle swarm optimization." Information Sciences, 436–437, 441–465. https://doi.org/10.1016/j.ins.2018.01.038.