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A performance evaluation indicator system and method for manufacturing-integrated generative design

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Abstract. Generative design can explore a broad design space under specified performance and manufacturing constraints, yet its optimization objectives often emphasize component-level properties while giving limited consideration to manufacturing cost, environmental impact, and design-manufacturing coordination. This paper proposes a manufacturing-integrated performance assessment framework that embeds these concerns in the generative design process. The framework comprises four dimensions: technical feasibility, economic rationality, green sustainability, and process coordination. It maps measurable indicators from these dimensions to design objectives, hard constraints, and post-generation evaluation criteria. A two-stage decision procedure is proposed: Pareto-based screening first retains non-dominated alternatives, and a subsequent multi-criteria decision method ranks the retained candidates according to stakeholder preferences and indicator information. A performance-driven workflow is then illustrated using two industrial cases. In the wheel-hub case, a multimodal generation and prediction pipeline combines a conditional generative adversarial network with two- and three-dimensional variational autoencoders and finite-element analysis. The reported test results include a mean absolute percentage error of 2.79% for equivalent-stress prediction and an inference time of approximately 2.5s. A separate illustrative Pareto exercise uses synthetic data and is therefore treated only as a demonstration of the decision procedure. In the aircraft-bracket case, the optimized additively manufactured design reduces component mass by 46.2% and lifecycle cost by 39.50%, although unit manufacturing cost increases by 39.47%. These cases demonstrate why generative design should be assessed across the design-to-manufacturing lifecycle rather than by a single performance metric.

Keywords: generative design, manufacturing performance assessment, multi-objective optimization, lifecycle cost, design for manufacturing

1. Introduction

Generative design has become an important approach to product development because it can automatically explore alternative geometries in response to specified objectives, design spaces, material properties, and manufacturing constraints. Combined with topology optimization, machine learning, and advanced manufacturing, it can support lightweight structures and complex components that may be difficult to identify through conventional experience-led iteration. However, a design that performs well in a simulation is not

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necessarily the best choice for production. A geometrically efficient structure may require expensive processing, additional supports or post-processing, difficult inspection, or repeated redesign before it can be manufactured reliably.

This gap reflects a broader limitation in conventional performance assessment. Product design, process planning, manufacturing, and lifecycle evaluation are often managed as separate activities. Technical metrics such as stress, stiffness, and mass are assessed during design, whereas cost, energy use, emissions, process compatibility, and coordination effort may be considered only after a candidate has been selected. Such a sequence can produce local optima: a component can be lighter but more expensive to manufacture, or theoretically efficient but poorly matched to available equipment and downstream operations.

Prior research has addressed sustainability-oriented factory layout, design and manufacturing optimization, generative-design variability, and trade-offs among manufacturing processes [1-9]. Work on sustainable manufacturing performance has also emphasized the importance of multiple stakeholders and broader evaluation criteria [10]. Nevertheless, a practical connection between a multidimensional manufacturing-performance system and the generation, screening, and selection of design alternatives remains necessary. In particular, indicators need to be translated into computable objectives and constraints rather than retained as a post hoc scorecard.

This paper develops a manufacturing-integrated performance assessment framework for generative design. Its principal contribution is methodological: it organizes indicators into four connected dimensions and specifies how they can be incorporated into a closed-loop workflow that links candidate generation, constraint checking, performance estimation, multi-objective screening, decision support, and feedback. Two industrial illustrations are used to clarify the framework's operation and its implications.

2. Framework and methodology

2.1. Four dimensions of manufacturing-integrated performance

The proposed framework evaluates a design as part of a manufacturing system, not merely as a geometric object. The four dimensions are complementary and should be adapted to the product, manufacturing route, and available evidence.

Technical feasibility concerns whether a candidate can satisfy functional and engineering requirements. Potential indicators include maximum equivalent stress, safety factor, fatigue life, stiffness, deformation, dimensional accuracy, and compatibility with the intended manufacturing process. Safety-critical requirements should normally be implemented as hard constraints, because a low cost or environmental score cannot compensate for an unacceptable structural failure.

Economic rationality captures the resources required to design, manufacture, assemble, operate, maintain, and retire a product. Depending on the application, indicators can include material cost, processing cost, equipment use, assembly cost, rework, unit manufacturing cost, and lifecycle cost. A lifecycle perspective is important when an alternative has a higher initial production cost but may deliver benefits during use or maintenance.

Green sustainability represents resource consumption and environmental burdens. Relevant indicators include material utilization, energy consumption, greenhouse-gas emissions, waste generation, and end-of-life recovery. Where a full life-cycle assessment is not supported by data, the assessment should explicitly report the available system boundary and avoid presenting unmeasured environmental benefits as established results.

Process coordination evaluates the compatibility and continuity of design and manufacturing activities. Candidate indicators include the number of design-manufacturing iterations, process-chain length, data-

exchange efficiency, manufacturing preparation effort, post-processing requirements, and the successful transfer of a design into a verified physical component. These indicators help reveal implementation risks that may not be visible in geometry-based optimization.

Table 1 summarizes evaluation indicators. The list is not intended as a universal fixed checklist; but the indicators are selected according to their relevance, measurability, independence, and availability for the case under study.

Table 1. Evaluation indicators for 4 dimensions

Dimension	Evaluation indicators	Typical evaluation direction
Technical feasibility	Maximum stress; safety factor; fatigue life; stiffness; process compatibility	Minimize stress; satisfy safety and functional limits
Economic rationality	Material and processing cost; unit cost; lifecycle cost; rework cost	Minimize cost subject to required performance
Green sustainability	Material utilization; energy use; emissions; waste	Increase utilization; minimize energy, emissions, and waste
Process coordination	Iteration count; process-chain length; post-processing; data-transfer performance	Reduce iterations and unnecessary process steps; improve transferability

2.2. Indicator normalization and weighting

Indicators are expressed in different units and may have opposite preference directions. Before aggregation, each indicator should therefore be normalized to a common interval, such as [0, 1]. For a benefit-type indicator, where a larger value is preferred, min-max normalization can be written as

$$z_{ij} = (x_{ij} - minx_{ij})/(maxx_{ij} - minx_{ij}). \tag{1}$$

For a cost-type indicator, where a smaller value is preferred, the direction is reversed:

$$z_{ij} = (maxx_{ij} - x_{ij})/(maxx_{ij} - minx_{ij}). \tag{2}$$

Here, x_{ij} denotes the raw value of indicator j for candidate i, and z_{ij} is its normalized value. If the maximum and minimum are equal, the indicator provides no discrimination among the candidates and requires a predefined handling rule. For engineering thresholds, normalization must not replace feasibility checking: a candidate that violates a mandatory stress or safety limit should be excluded or flagged before preference-based ranking.

A combined weighting approach can integrate expert preference with information from the candidate data. Analytic Hierarchy Process (AHP) weights represent structured stakeholder judgments, while entropy weights represent the relative information variation of the observed alternatives. A linear combination can be expressed as $w_j = \alpha w_j^s + (1 - \alpha)w_j^o$, where w_j^s and w_j^o denote subjective and objective weights, respectively, and $\alpha \in [0, 1]$ controls their relative influence. Weight sensitivity should be examined because changes in preferences or candidate composition may alter the final ranking.

2.3. Pareto screening and final decision

Because the four dimensions can conflict, a single weighted score should not be used to eliminate alternatives too early. Let a candidate design be represented by x and let $f(x) = [f_1(x), \ldots, f_m(x)]$ be the set of objectives to be minimized. A feasible candidate x^a dominates x^b if $f_j(x^a) \leq f_j(x^b)$ for every objective j and the inequality is strict for at least one objective. The Pareto set contains feasible candidates that are not

dominated by another candidate. This set preserves meaningful trade-offs, for example between mass and cost, rather than assuming that one solution is best under all conditions.

The proposed decision process has two stages. First, engineering constraints are applied and Pareto non-dominated candidates are retained. Second, the retained candidates are ranked using a multi-criteria method such as TOPSIS. In TOPSIS, each candidate is compared with a positive ideal solution and a negative ideal solution, and a relative-closeness score is calculated. The score supports selection according to the chosen indicators and weights; it does not eliminate the need for engineering judgment or uncertainty analysis.

The complete workflow consists of (1) defining requirements and manufacturing conditions; (2) generating candidate designs; (3) checking geometric, material, process, and safety constraints; (4) estimating performance using simulation, prediction models, or physical tests; (5) normalizing indicators and constructing the feasible objective space; (6) identifying Pareto non-dominated candidates; (7) ranking candidates under explicit preferences; and (8) feeding validation findings back into design rules, indicators, and algorithm settings. Each iteration should retain records of inputs, model versions, predicted and observed performance, and reasons for accepting or rejecting a candidate.

3. Industrial illustrations

3.1. Wheel-hub design: performance-driven generation and assessment

3.1.1. Overall architecture

We developed a five-layer workflow for performance-driven wheel-hub design: a wheel-hub module image library, multimodal design generation, intelligent engineering assessment, integrated performance evaluation, and dynamic evolution. The image library stores wheel-hub form semantics, line features, sketches, and design images. A conditional Generative Adversarial Network (cGAN) generates candidate designs from semantic conditions and sketches. A coupled two-dimensional/three-dimensional prediction model then estimates engineering responses. The resulting candidates are evaluated in terms of technical feasibility, economic rationality, green sustainability, and process coordination, before Pareto screening and TOPSIS-based selection. An AI-agent feedback mechanism is incorporated to support subsequent updates to the indicator system and the generation procedure.

The wheel-hub image library represents seven semantic categories: compact and professional, robust, romantic, streamlined and futuristic, exaggerated, soft and elegant, and simple. The design vocabulary is organized around seven elements: overall configuration, bolt-hole type, spoke-front shape, spoke number, spoke-edge treatment, spoke width, and center-disc form. These elements are further divided into 20 subtypes. Linking semantic labels with geometric features establishes a semantic-feature-performance mapping for subsequent generation and assessment.

For this case, technical indicators include maximum equivalent stress, safety factor, fatigue life, stiffness, and process compatibility. Economic indicators include material, processing, assembly, and total manufacturing costs. Green indicators include carbon emissions, material utilization, energy use, and waste. Process-coordination indicators include design-manufacturing iterations, process-chain length, data-exchange efficiency, and collaborative project success.

3.1.2. Implementation

Wheel-hub sample screening and image-library construction. We collected 1,240 wheel designs covering passenger cars, SUVs, MPVs, and commercial vehicles. Each image was standardized to a frontal 90° view; backgrounds and brand marks were removed; and images were converted to grayscale at 512 × 512 pixels. A

Variational Autoencoder (VAE) mapped the images into a latent feature space. DBSCAN was then applied with Eps = 0.9 and $MinPts$ = 5, identifying seven shape clusters. Ten representative samples were selected from each cluster, yielding 70 representative wheel-hub samples. Each library entry contains a sketch, original image, feature annotations, and semantic labels.

Multimodal design generation. We used a cGAN as the wheel-hub generation engine. The generator takes a semantic condition and random noise as inputs and outputs a wheel-hub image, while the discriminator performs both semantic classification and authenticity discrimination. The network comprises semantic encoding, cross-domain image transformation, and image-space regularization. Training combines adversarial, sketch-domain, and semantic losses.

Intelligent engineering assessment. The prediction model fuses a two-dimensional convolutional VAE and a three-dimensional convolutional VAE. The 2D branch processes 128 × 128 frontal images, whereas the 3D branch processes 64 × 64 × 64 voxel representations. Their fused features are used to predict maximum equivalent stress, its three-dimensional location, and stress-distribution information. We used 1,000 wheel-hub samples, divided into 700 training, 150 validation, and 150 test samples. The loss function accounts for coordinate error, stress-prediction accuracy, and stress-distribution similarity.

The engineering assessment uses A356 aluminum alloy. Its material properties are: Young's modulus, 72 GPa; yield strength, 230 MPa; Poisson's ratio, 0.33; ultimate tensile strength, 290 MPa; and density, 2.68 × 10^{-6} kg/mm³. The assessment conditions include a bending-fatigue moment of 1,660 Nm, a radial load of 8,000 N, and an impact hammer mass of 150 kg released from 600 mm. The corresponding stress thresholds are 135 MPa for bending, 140 MPa for radial loading, and 220 MPa for impact. Cost indicators are estimated using parameterized cost models; energy, emissions, material utilization, and waste are intended to be quantified using life-cycle assessment; and process-coordination indicators are obtained through process analysis and digital-thread data.

Pareto optimization and integrated decision-making. We use design constraints, manufacturing constraints, and the four performance dimensions as inputs to the Performance-Driven Generative Design (PDGD) procedure. Candidate designs are generated and evaluated, infeasible candidates are removed, and non-dominated alternatives are retained. The retained alternatives are then ranked using combined AHP-entropy weights and TOPSIS. Subjective weights represent decision-maker preferences, while entropy weights reflect the information variation among candidate designs. The combined weight is calculated as $w = \alpha w_{sub} + (1 - \alpha) w_{obj}$.

Dynamic feedback. We incorporate an AI-agent mechanism to identify indicator gaps and update the PDGD procedure. The curiosity mechanism explores boundary cases and new materials; the self-repair mechanism detects conflicting, redundant, or ineffective indicators; and knowledge transfer introduces indicators associated with emerging materials, processes, and regulations. Examples include anisotropic utilization for composite wheels, carbon-related costs under new regulatory requirements, and overhang-angle compliance for additive manufacturing.

3.1.3. Results and performance evaluation

Generation quality. We evaluated the generated wheel-hub designs in terms of semantic consistency, shape completeness, and sketch conformity. The mean scores were 4.05 for semantic consistency, 3.95 for shape completeness, and 4.00 for sketch conformity. At the system level, the proposed model achieved an SSIM of 0.86, feature fidelity of 0.91, and design-intent conformity of 0.89 in our comparison with GAN, VAE, and diffusion-model baselines.

Prediction accuracy and computational efficiency. On the 150-sample test set, the multimodal model achieved a mean three-dimensional location error of 30.19 mm and a median error of 23.43 mm. The

corresponding relative errors were 6.49% and 5.02%. The mean absolute percentage error for equivalent-stress prediction was 2.79%, and the root mean square error for stress distribution heatmaps was 0.0435. Prediction required approximately 2.5 s per design after training. These results support rapid preliminary screening; detailed finite-element analysis and physical testing remain necessary for final engineering verification.

Pareto-front demonstration. Because a complete measured dataset covering all four performance dimensions was not available for the same wheel-hub candidates, we used synthetic data to test the Pareto procedure. Sixty candidate records were generated with manufacturing cost and maximum equivalent stress as competing minimization objectives. Non-dominated sorting retained 11 candidates. The resulting front illustrates the trade-off between lower manufacturing cost and lower stress. Figure 1 presents the illustrative Pareto front for wheel-hub design.

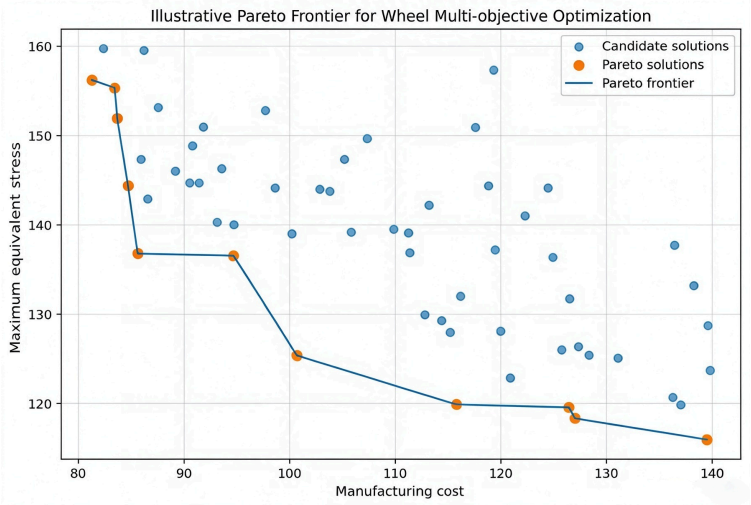


Figure 1. Illustrative Pareto front for wheel-hub design

After Pareto screening, the retained candidates can be ranked using the combined weights and TOPSIS. This second stage makes the decision-maker's preferences explicit while preserving non-dominated alternatives during the first stage.

3.1.4. Further optimization

The wheel-hub workflow can be improved in four directions. First, the cGAN architecture and loss-weight strategy can be refined to improve image clarity, structural completeness, and semantic consistency. Second, the prediction model can be strengthened through more diverse training samples, improved 2D–3D feature fusion, and refined finite-element meshes and boundary conditions. Third, the indicator system can be updated as new materials, manufacturing processes, and regulatory requirements emerge, with version control to preserve traceability. Fourth, configuration templates can be developed for casting, machining, and additive manufacturing, so that indicator weights and process constraints reflect the requirements of each production context.

3.2. Aircraft bracket: integrated assessment of lightweight design and manufacturing

3.2.1. Overall architecture

We selected the publicly documented aircraft-bracket case from the Direct Manufacturing Research Center (DMRC), Paderborn University, to examine the application of the integrated assessment framework. The bracket connects a luggage-compartment damper to the fuselage structure. The baseline component is

manufactured by conventional milling. The alternative is redesigned through topology optimization and design-for-additive-manufacturing principles, then produced by additive manufacturing and tested under different loading conditions.

We organized the assessment around five linked stages: design generation, manufacturing constraints, physical manufacturing, performance evaluation, and feedback. Technical performance is represented by component mass and the satisfaction of loading requirements; economic performance by unit manufacturing cost and lifecycle cost; green performance by material and resource use; and process coordination by manufacturing compatibility, post-processing requirements, and physical verification. The available numerical evidence supports mass and cost comparisons, while environmental performance is discussed only qualitatively because complete energy and emissions data are unavailable.

3.2.2. Implementation

The implementation follows six stages. First, we define the functional requirements, loading conditions, material properties, design space, and manufacturing constraints, using the milled bracket as the baseline. Second, topology optimization generates alternative lightweight geometries. Third, candidate designs are screened against structural requirements and additive-manufacturing constraints, including support and post-processing needs. Fourth, the selected design is manufactured and tested under the required loading conditions. Fifth, the baseline and optimized alternatives are compared across technical, economic, and design–manufacturing coordination dimensions. Finally, test and assessment findings are fed back into the design and manufacturing settings when further improvement is required.

3.2.3. Results and performance evaluation

Technical performance. The mass of the milled baseline bracket was 29.98 g. After topology optimization and additive manufacturing, the optimized bracket weighed 16.13 g, a reduction of 13.85 g or 46.2%. The manufactured bracket was also subjected to load testing, linking the computational redesign to physical verification.

Economic performance. Unit manufacturing cost increased from €66.11 for the milled bracket to €92.19 for the additively manufactured alternative, an increase of €26.08 or 39.47%. However, lifecycle cost decreased from €845.57 to €511.57, a reduction of €334.00 or 39.50%. The comparison shows that a higher unit manufacturing cost does not necessarily imply lower economic value over the lifecycle.

Process coordination and green performance. The optimized geometry was adapted to additive-manufacturing requirements before production, and the manufactured component underwent load testing. This provides qualitative evidence that the design was transferred into a physical manufacturing process and verified. The material-mass reduction is 13.85 g; however, it should not be interpreted as a quantified reduction in energy use or carbon emissions. A complete environmental comparison would require consistent process energy, material yield, support-material, and lifecycle-emissions data.

The bracket case therefore presents a clear multi-objective trade-off: the optimized design achieves substantial lightweighting and lower lifecycle cost, but its unit manufacturing cost is higher. Assessing the design solely by mass or unit cost would overlook part of its overall performance.

3.2.4. Further optimization

Further improvement should focus on the project implementation process as well as the component design. Feasibility checks can be moved earlier to eliminate unsuitable candidates before manufacturing preparation. Design, simulation, process planning, and quality personnel should participate in joint candidate reviews, while equipment, materials, and testing resources should be scheduled according to project stages. Future assessments should also collect consistent data on support material, post-processing time, machine utilization, energy consumption, and emissions to strengthen the environmental and process-coordination dimensions.

Taken together, the two cases illustrate complementary parts of the framework. The wheel-hub case demonstrates semantic design generation, multimodal performance prediction, and Pareto-based decision support, while the aircraft-bracket case demonstrates the trade-off between lightweighting, unit manufacturing cost, and lifecycle cost. The synthetic wheel-hub Pareto exercise is kept separate from measured or model-tested results, and the aircraft-bracket environmental implications are not quantified in the absence of complete lifecycle data.

4. Discussion

4.1. From component optimization to manufacturing-integrated decision-making

The framework changes the role of performance assessment from an endpoint to an active part of design exploration. By connecting indicators with objectives and constraints, it enables manufacturing concerns to influence candidate generation and selection rather than being considered only after a geometry has been chosen. This is consistent with design-for-manufacturing principles and with research that considers sustainability and manufacturing trade-offs in generative design.

The four dimensions also help distinguish non-negotiable requirements from preference-dependent trade-offs. Safety, functional performance, and mandatory process limits should be treated as feasibility conditions. Cost, environmental burden, and coordination effort can then be optimized or compared among feasible candidates. Pareto screening preserves alternatives with different strengths, while a subsequent ranking step makes stakeholder preferences explicit. This combination is more informative than using a single weighted sum from the beginning.

4.2. Data quality, uncertainty, and interpretability

The framework depends on the quality and comparability of its input data. Prediction models can reduce the time required for preliminary evaluation, but their errors must be assessed against suitable validation data and the model should be used within its supported domain. Final acceptance of safety-critical parts still requires appropriate high-fidelity simulation, inspection, and physical testing. Similarly, cost and environmental indicators should use clearly stated system boundaries, data sources, units, and assumptions.

Indicator weights introduce another source of uncertainty. Expert preferences may differ across manufacturers, product families, or production volumes, while entropy weights depend on the candidate set and the variation observed in the data. Sensitivity analysis should therefore test whether the recommended alternative remains stable under plausible changes in weights, costs, manufacturing assumptions, and predicted performance. If rankings change substantially, the decision-maker should be shown the competing alternatives and the conditions under which each becomes preferable.

4.3. Limitations and implementation priorities

Although the proposed framework provides a structured approach to manufacturing-integrated generative design, several limitations remain. In the wheel-hub case, the performance prediction model demonstrates promising accuracy and computational efficiency. However, the multi-objective Pareto analysis is based on synthetic candidate data and therefore illustrates the decision-making procedure rather than verified improvements in actual manufacturing performance. In the aircraft-bracket case, the available results demonstrate improvements in component mass and lifecycle cost, but further quantitative assessment of energy consumption and carbon emissions is required to establish its full environmental benefits.

Future research should focus on developing more comprehensive datasets that connect design characteristics with engineering performance, manufacturing costs, environmental impacts, and process-coordination information. Further efforts are also needed to improve the reliability of performance prediction, examine the sensitivity of decision results to indicator weights, and validate the framework across different products and manufacturing processes. These improvements would strengthen the practical applicability and reproducibility of the proposed approach.

5. Conclusions

This paper proposed a manufacturing-integrated performance assessment framework for generative design based on technical feasibility, economic rationality, green sustainability, and process coordination. The framework connects indicators to design objectives and constraints, applies feasibility screening and Pareto analysis to retain non-dominated candidates, and uses multi-criteria ranking to support final selection. A feedback loop links design generation, performance evaluation, manufacturing verification, and subsequent refinement.

This paper proposed a manufacturing-integrated performance assessment framework for generative design, incorporating four complementary dimensions: technical feasibility, economic rationality, green sustainability, and process coordination. By integrating performance indicators into design generation, feasibility assessment, Pareto-based optimization, and multi-criteria decision-making, the framework provides a systematic approach to evaluating design alternatives beyond conventional component-level performance criteria.

The two industrial illustrations demonstrate the potential applications of the proposed framework. The wheel-hub case integrates semantic design generation with multimodal performance prediction, providing support for efficient early-stage design screening. The aircraft-bracket case further illustrates the trade-offs between lightweight design, manufacturing cost, and lifecycle value. In particular, the reduction in component mass and lifecycle cost, despite an increase in unit manufacturing cost, highlights the importance of multidimensional performance assessment in design decision-making.

This study contributes to connecting generative design with broader manufacturing performance requirements. By bringing manufacturing considerations into the early stages of design exploration, the proposed framework can help designers identify more balanced alternatives, improve design-to-manufacturing integration, and support more informed product development decisions. Future research will focus on comprehensive empirical validation using integrated technical, economic, environmental, and process data.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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