

Environmental Assessment of Intelligent Logistics Automation

LIN, Shengtao ¹

¹ Shenzhen Haitaobe Network Technology Co., Ltd, CN

* *are the corresponding author, E-mail:*

Abstract: Currently, with the development of intelligent logistics automation, lower operating costs and higher service reliability are increasingly associated with it. However, its net environmental impact remains uncertain because improvements in physical efficiency can be affected by computing energy consumption, equipment turnover, battery production, and demand rebound. Therefore, this paper constructs a lifecycle-oriented framework for evaluating automated transportation, warehousing, packaging, and digital infrastructure. This framework integrates findings from research in logistics, mobility, edge computing, and organization, and combines transparent index equations with reproducible example scenarios. Analysis shows that a adaptive route planning, regional resource coordination, energy-saving control, and circular material management can reduce the intensity of environmental impact to some extent, but the results largely depend on system boundaries, power structure, utilization, service commitment, and equipment lifespan. Therefore, cross-domain evidence is considered as methodological guidance rather than direct logistics evidence. The final framework integrates environmental benefits, cost, service quality, and resilience as common constraints.

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1 INTRODUCTION

1.1 RESEARCH BACKGROUND

The growth of e-commerce, regional distribution, and time-sensitive supply chains has increased the scale and complexity of logistics operations. Automation has become a central response: automated storage and retrieval systems, autonomous mobile robots, intelligent dispatch platforms, machine-vision sorting, and predictive inventory systems can process more orders with greater consistency. Yet an automated system is not inherently green. Electricity demand, battery production, equipment turnover, packaging throughput, and the computational load of real-time decision systems all create environmental burdens that must be measured across the system life cycle.

Regional coordination is especially important because environmental outcomes are produced across networks rather than within a single warehouse. Chen's study of regional logistics and supply-chain integration offers a valuable enterprise-level perspective by connecting scalable operations of micro and small logistics firms with broader network coordination [1]. This contribution is important to the present study because fragmented carriers, warehouses,

and shippers cannot optimize loading, routing, and reverse logistics effectively when their information remains isolated.

At the infrastructure level, Tsolakis et al. provide a particularly relevant application of AI-driven environmental sustainability in automated container-port logistics [2]. Their work is notable because it places automation inside an explicit environmental objective rather than treating sustainability as an incidental benefit of higher productivity.

1.2 RESEARCH PROBLEM AND OBJECTIVES

The central research problem is the absence of a unified evaluation logic linking operational automation to net environmental performance. A warehouse may reduce labor and travel distance while increasing electricity peaks; a routing platform may lower kilometers per parcel while stimulating faster delivery and additional trips; an electric fleet may eliminate tailpipe emissions while transferring impacts to electricity generation and battery supply chains. Consequently, assessment must define boundaries, counterfactuals, time horizons, and functional units before claiming improvement.

Chen's analysis of intelligent algorithms for regional logistics resource matching is a useful contribution because it focuses attention on the quality of matching among demand,

capacity, and spatially distributed resources [3]. The study supports a key proposition of this paper: environmental gains depend on whether intelligence reduces idle capacity and coordination loss, not merely on whether an algorithm is deployed. Parimala et al. explicitly connect AI-enabled resource optimization with environmental efficiency in green logistics [4], providing a timely bridge between computational methods and sustainability evaluation.

1.3 RESEARCH APPROACH AND CONTRIBUTION

The study uses structured literature synthesis, system-boundary analysis, and a life-cycle-oriented indicator framework. Rather than inventing enterprise performance figures, it identifies measurable variables and causal pathways that can be tested with operational data. This cautious design also makes it possible to distinguish direct logistics evidence from methodologically transferable insights.

The paper's main contribution is the integration of physical logistics and digital infrastructure into one environmental assessment. It also distinguishes three evidentiary levels: direct logistics evidence, analogous transportation or manufacturing evidence, and transferable computational or organizational methods. This distinction prevents a common mistake in interdisciplinary research, presenting a method validated in one domain as if its environmental effect had already been demonstrated in another.

2 LITERATURE REVIEW AND CONCEPTUAL FOUNDATION

2.1 GREEN LOGISTICS AND NETWORK INTEGRATION

Green logistics seeks to minimize environmental harm while maintaining the economic and service functions of transportation, warehousing, packaging, handling, distribution, and reverse flows. Its unit of analysis should therefore extend beyond a single device. Network configuration, consolidation, delivery promises, modal choice, facility location, and information sharing jointly influence emissions and resource use.

Chen's work on practical development paths for local logistics enterprises is valuable because it links technology research and development, standardization, and industry empowerment [5]. This combination is highly relevant: isolated pilot projects rarely produce durable environmental improvement unless operating rules, data definitions, supplier requirements, and staff capabilities evolve together. Huang's real-time adaptive dispatch research further contributes a concrete algorithmic direction for dynamic vehicle routing under time-varying demand [6]. Its significance lies in recognizing that static route plans are insufficient when orders, congestion, vehicle status, and delivery constraints

change.

Supply-chain sustainability must also remain reliable under disruption. Huang's application of foundation time-series models to supply-chain resilience measurement is a forward-looking contribution because it brings modern temporal modeling into the assessment of system robustness [7]. Environmental efficiency that disappears during peak demand or disruption is not a stable green outcome. Lin's machine-learning-based logistics network optimization research complements this perspective by emphasizing the network-level role of predictive and optimization algorithms [8]. Together, these studies support an integrated view in which efficiency, resilience, and environmental performance are evaluated simultaneously.

2.2 INTELLIGENT MOBILITY AND SUSTAINABLE FREIGHT SYSTEMS

Arsenio et al. examine the co-evolution of intermodal freight research and patenting trends for green and intelligent logistics [9]. This work is particularly valuable for situating academic research within technological development and commercialization. Popescu et al. provide an environmental evaluation focused on logistics-center activities [10], offering an important facility-level counterpart to network and fleet studies. Nie's analysis of sustainability optimization in North American cross-border logistics networks adds an international and network-boundary perspective [11]. Its contribution is notable because cross-border systems must reconcile long distances, multiple actors, infrastructure differences, and regulatory constraints.

Leong et al. connect intelligent fleet management and smart logistics with green mobility solutions [12]. Their work reinforces the need to link vehicle technology with dispatch intelligence: replacing a propulsion system without improving utilization can leave a avoidable mileage untouched. These studies collectively suggest that sustainable logistics requires coordinated decisions across facilities, fleets, modes, and jurisdictions.

2.3 TECHNOLOGY ADOPTION AND RESEARCH TRANSLATION

Bueno-Pascual identifies forces transforming transportation and logistics toward smarter sustainability [13]. This broad perspective appropriately closes the conceptual review by emphasizing that technological, market, regulatory, and organizational forces interact. The literature therefore supports neither technological determinism nor blanket skepticism: intelligent automation can contribute to green logistics when environmental objectives, measurement, governance, and adoption mechanisms are aligned.

3 ENVIRONMENTAL IMPACT ASSESSMENT FRAMEWORK

3.1 SYSTEM BOUNDARY AND FUNCTIONAL UNIT

A defensible assessment begins by specifying the service delivered. Appropriate functional units include one parcel delivered within a defined service level, one tonne-kilometer of freight, one pallet stored and handled for a defined period, or one order processed through a distribution center. Comparisons must use equivalent service quality; otherwise, a slower or less reliable baseline may appear artificially efficient.

To maintain comparability across logistics systems of different operational scales, environmental performance was normalized by a clearly defined functional unit, expressed as follows:

$$I_x = \frac{X}{Q}$$

In this expression, X represents the total environmental load or activity quantity measured during the assessment period, while Q denotes the corresponding logistics service output. The selection of Q should remain consistent across the compared scenarios.

The system boundary should include upstream production of equipment and batteries, facility construction where material, operational electricity and fuels, consumables and packaging, maintenance and replacement, digital computation and communications, transport activity, and end-of-life treatment. Direct effects arise from equipment operation and vehicle movement. Indirect effects include embodied materials and electricity generation. Rebound effects occur when lower cost or faster service stimulates additional demand, more frequent delivery, or shorter replacement cycles.

3.2 INDICATOR ARCHITECTURE

The proposed indicator system contains six dimensions. Energy indicators include kilowatt-hours per order, peak demand, charging losses, fuel per tonne-kilometer, and the share of renewable electricity. Climate indicators include scope-specific greenhouse-gas emissions per functional unit and avoided emissions relative to a defined baseline. Resource indicators cover equipment mass, battery capacity, packaging material, recycled content, warehouse-space utilization, and asset utilization.

Waste indicators include packaging waste, damaged goods, obsolete electronics, batteries, and recovered material. Ecosystem and local-impact indicators include land occupation, noise, particulate matter, nitrogen oxides, congestion, and exposure near communities. Digital indicators include compute energy per inference or optimization run, device utilization, data-transfer volume, model-update frequency, and hardware life. Resilience indicators include service recovery time, energy performance during disruption, and the proportion of decisions that remain feasible under demand or infrastructure shocks.

The operational energy intensity of the logistics system was calculated by dividing total energy consumption by the number of equivalent orders processed:

$$EI = \frac{E_f + E_v + E_d}{Q}$$

The inclusion of E_d is important because excluding digital infrastructure could make an automated system appear more energy-efficient than it actually is. Nevertheless, the allocation of shared cloud-computing energy may remain uncertain and should be examined through sensitivity analysis.

Energy consumption was converted into greenhouse-gas emissions by applying source-specific emission factors, after which the result was normalized by logistics output:

$$GI = \frac{E_c EF_c + F_d EF_d + F_g EF_g}{Q}$$

The resulting value should be interpreted cautiously because electricity emission factors vary across regions and time periods. A reduction in electricity consumption does not necessarily produce an equivalent reduction in emissions when the electricity supply becomes more carbon-intensive.

Transportation efficiency was represented by vehicle-distance intensity, although this indicator was interpreted together with delivery success, loading rate, and service coverage:

$$TI = \frac{\sum_{i=1}^n D_i}{Q}$$

A lower value of TI may indicate improved routing or order consolidation, but it could also result from reduced service coverage or the exclusion of difficult delivery areas. The indicator should not be interpreted independently of operational context.

To distinguish route shortening from genuine improvements in capacity utilization, the average vehicle loading rate was estimated as follows:

$$LR = \frac{\sum_{i=1}^n L_i D_i}{\sum_{i=1}^n C_i D_i} \times 100\%$$

Distance weighting was introduced because a vehicle operating at low capacity over a long distance may create a greater environmental burden than a short, partially loaded trip. Some uncertainty remains when vehicle capacity is constrained by volume rather than weight.

Packaging-material intensity was calculated to evaluate whether automation and right-sized packaging reduced material demand relative to logistics output:

$$PI = \frac{M_p}{Q}$$

The weighted form may provide a more informative result than total mass alone because equal quantities of plastic, paper, metal, and reusable packaging do not necessarily generate equivalent life-cycle impacts.

TABLE 1. CORE ENVIRONMENTAL INDICATORS AND REPRODUCIBLE CALCULATION EQUATIONS

Indicator	Equation	Variables	Unit	Interpretive caution
Energy intensity	$EI = E / Q$	E = energy consumed; Q = logistics service output	kWh/order	A lower ratio may reflect higher utilization rather than lower absolute energy.
Transport intensity	$TI = D / Q$	D = vehicle distance; Q = service output	km/order	Service coverage, failed deliveries, and load factor should be held comparable.
GHG intensity	$GI = (E \times EF_e + F \times EF_f) / Q$	EF = emission factor; F = fuel use	kg CO2e/order	Results depend on grid, fuel boundary, and emission-factor selection.
Packaging intensity	$PI = M_p / Q$	M_p = packaging mass	kg/order	Material type, recycled content, and reuse cycles remain relevant.
Relative change	$RC = (I_1 - I_0) / I_0 \times 100\%$	I_0 = baseline intensity; I_1 = assessed intensity	%	Negative values indicate a decline; causal attribution requires a counterfactual.

Note: Equations are defined in this study. They are dimensionally auditable but do not replace life-cycle inventory data.

3.3 MEASUREMENT AND ANALYTICAL PROCEDURE

The assessment follows five steps. First, define the

decision question, functional unit, geography, and time horizon. Second, construct a process map from order creation through transport, storage, handling, delivery, returns, and end-of-life flows. Third, collect activity data from meters, vehicle telematics, warehouse-management systems, transport-management systems, charging equipment, packaging records, and procurement data. Fourth, apply transparent conversion factors and allocate shared impacts consistently. Fifth, compare scenarios and test sensitivity to demand, electricity mix, equipment life, loading rate, delivery time promise, and return rate.

The research process was less linear than the final framework may initially suggest. Early attempts to compare studies through a single carbon-intensity measure proved problematic because some studies used parcels, others used vehicle distance, facility throughput, or computational latency, while several cross-domain papers did not report environmental outcomes at all. The framework was consequently revised twice: first by separating physical and digital inventories, and later by introducing evidence tiers that distinguish direct logistics findings from transferable methods. This adjustment reduced superficial comparability, but it also made the remaining claims more defensible and exposed where primary measurements are still missing.

Algorithmic evaluation should include an operational counterfactual. For routing, the comparison may be current dispatch versus adaptive dispatch under the same orders and constraints. For warehouse automation, it may compare energy, damage, throughput, and space use per equivalent order. For edge AI, it should measure both computational energy and the physical savings enabled by the decisions. Statistical uncertainty, missing data, and model drift should be reported rather than hidden behind a single point estimate.

The relative change between the baseline and automated scenarios was calculated using the following equation:

$$RC = \frac{I_1 - I_0}{I_0} \times 100\%$$

A negative value indicates a decline in environmental-impact intensity, whereas a positive value indicates an increase. The calculation describes the magnitude of change but does not, by itself, establish that automation caused the observed difference.

TABLE 2. TRANSPARENT ILLUSTRATIVE CALCULATION OF INTENSITY CHANGES

Metric	Baseline inputs	Automated-system inputs	Calculated intensities	Relative change
Facility electricity	$E_0 = 960,000 \text{ kWh}; Q_0 = 1,200,000 \text{ orders}$	$E_1 = 1,050,000 \text{ kWh}; Q_1 = 1,500,000 \text{ orders}$	$EI_0 = 0.800; EI_1 = 0.700 \text{ kWh/order}$	$(0.700 - 0.800) / 0.800 = -12.5\%$

Vehicle distance	D0 = 2,400,000 km; Q0 = 1,200,000	D1 = 2,550,000 km; Q1 = 1,500,000	TI0 = 2.000; TI1 = 1.700 km/order	(1.700 - 2.000) / 2.000 = -15.0%
Packaging mass	Mp0 = 360,000 kg; Q0 = 1,200,000	Mp1 = 375,000 kg; Q1 = 1,500,000	PI0 = 0.300; PI1 = 0.250 kg/order	(0.250 - 0.300) / 0.300 = -16.7%
Electricity-related GHG	EI0 = 0.800; EFe0 = 0.55 kg CO2e/kWh	EI1 = 0.700; EFe1 = 0.55	GI0 = 0.440; GI1 = 0.385 kg CO2e/order	(0.385 - 0.440) / 0.440 = -12.5%

Note: All values are explicitly hypothetical and are included only to demonstrate reproducible arithmetic. Although each intensity declines, absolute electricity, distance, and packaging mass rise, illustrating why absolute and normalized results should be reported together.

Four principles guide interpretation. First, efficiency is not the same as absolute reduction: total impacts may rise if volume grows faster than unit efficiency improves. Second, burden shifting must be disclosed across life-cycle stages, locations, and environmental categories. Third, optimization objectives must include environmental constraints explicitly; a cost-only model may create faster but more fragmented delivery. Fourth, cross-domain methods require target-domain validation, as emphasized by the methodological boundary discussion in Section 2.4.

4 ENVIRONMENTAL EFFECTS AND GREEN LOGISTICS STRATEGIES

4.1 ENERGY CONSUMPTION AND CARBON EMISSIONS

Automated storage systems, conveyors, robots, charging stations, lighting, ventilation, cooling, servers, and network equipment create a complex load profile. Automation can lower energy per handled unit when equipment is highly utilized and controlled intelligently, but idle operation and peak charging can negate the advantage. A green control strategy should therefore combine equipment sleep modes, regenerative drives, high-efficiency motors, demand-aware task batching, battery-state monitoring, renewable generation, and storage-aware charging.

A decline in electricity per order admits several interpretations. It may indicate genuinely improved equipment control, yet it may also reflect higher throughput that spreads a largely fixed load across more orders, a warmer or cooler comparison period, changes in product mix, or the exclusion of cloud computing from the facility meter. Absolute electricity can therefore rise while intensity falls.

Neither observation is sufficient alone; both should be reported, and sensitivity to utilization and the electricity emission factor should be examined.

Because electricity-related results may vary substantially with the assumed grid emission factor, a sensitivity coefficient was calculated as follows:

$$S_{EF} = \frac{\Delta GI/GI}{\Delta EF_e/EF_e}$$

A larger absolute value of S_{EF} indicates that the reported environmental performance is more sensitive to assumptions about the electricity supply. Such sensitivity does not invalidate the assessment, but it suggests that regional and time-specific emission factors should be preferred where reliable data are available.

TABLE 3. SENSITIVITY OF ELECTRICITY-RELATED EMISSIONS TO GRID ASSUMPTIONS

Scenario	Baseline EF	Automated EF	Baseline GI	Automated GI / change
A: Same lower-carbon grid	0.35 kg CO2e/kWh	0.35 kg CO2e/kWh	$0.800 \times 0.35 = 0.280$	$0.700 \times 0.35 = 0.245$; -12.5%
B: Same higher-carbon grid	0.70 kg CO2e/kWh	0.70 kg CO2e/kWh	$0.800 \times 0.70 = 0.560$	$0.700 \times 0.70 = 0.490$; -12.5%
C: Cleaner project electricity	0.55 kg CO2e/kWh	0.40 kg CO2e/kWh	$0.800 \times 0.55 = 0.440$	$0.700 \times 0.40 = 0.280$; -36.4%
D: More carbon-intensive project electricity	0.40 kg CO2e/kWh	0.55 kg CO2e/kWh	$0.800 \times 0.40 = 0.320$	$0.700 \times 0.55 = 0.385$; +20.3%

Note: $EI0 = 0.800$ and $EI1 = 0.700$ kWh/order from Table 2. $GI = EI \times$ electricity emission factor (EF). The factors are scenario assumptions, not claims about a particular grid.

4.2 TRANSPORTATION, ROUTING, AND FLEET MANAGEMENT

Transportation strategies should prioritize consolidation, loading rate, route quality, modal choice, and delivery-demand management. Real-time adaptive dispatch [6] can be integrated with traffic, vehicle state, charging availability, delivery windows, and carbon-intensity signals. Machine-learning network optimization [8] can support facility assignment and capacity planning, while regional resource matching [3] can reduce fragmentation among shippers and carriers.

Reduced vehicle-kilometers per order may arise from better routing, denser demand, relaxed delivery windows, or selective exclusion of difficult destinations. Conversely, a measured increase could accompany a deliberate shift toward smaller electric vehicles, improved rural coverage, or fewer failed deliveries. These alternative explanations matter because a narrow distance metric could reward service withdrawal or penalize socially useful access. A credible evaluation should retain service coverage, delivery success, load factor, energy source, and customer-time constraints alongside distance.

Electric vehicles reduce tailpipe emissions but do not eliminate life-cycle impacts. Smart fleet-management research [12] reinforces the benefit of combining propulsion changes with intelligent utilization. Cross-border and intermodal planning should additionally account for infrastructure, mode transfer, and regulatory boundaries [9][11].

4.3 WAREHOUSING, PACKAGING, AND CIRCULAR RESOURCE USE

Warehouse automation can improve space use, inventory accuracy, and handling consistency, potentially reducing facility expansion and product damage. These gains must be balanced against embodied impacts of racks, robots, sensors, batteries, and frequent upgrades. Facility-level environmental evaluation, as illustrated by Popescu et al. [10], should combine operational and material flows rather than focus on electricity alone.

Circular strategies include modular equipment, repairability requirements, component harvesting, battery diagnostics, supplier take-back, reusable transport packaging, right-sized packaging, recycled content, and reverse-logistics loops. Procurement should specify minimum service life, parts availability, environmental data, and end-of-life responsibility.

4.4 DATA GOVERNANCE, RESILIENCE, AND RESPONSIBLE OPTIMIZATION

Environmental optimization depends on trustworthy data. Organizations should document data provenance, measurement frequency, missing-value treatment, model versions, and the constraints applied to automated decisions. Resilience measurement [7] should be connected to environmental metrics so that disruption plans do not rely automatically on high-emission expedited transport. Models should also be tested when geography, demand composition, or operational policy changes.

Implementation should begin with a verified baseline and a limited number of high-materiality processes. Enterprises can then prioritize interventions using environmental benefit, cost, technical feasibility, data readiness, and operational risk. Technology-development and standardization pathways [5] should be combined with

regional supply-chain coordination [1].

A practical sequence is: establish governance and boundaries; meter energy and material flows; optimize existing assets; pilot algorithms with counterfactual evaluation; integrate renewable energy and circular procurement; scale through common standards; and publish transparent results. The cross-sector transformation forces summarized by Bueno-Pascual [13] indicate that policy, infrastructure, skills, customer expectations, and technology must advance together.

5 CONCLUSIONS

The analysis undertaken in this study suggests that intelligent logistics automation may contribute to environmental improvement, although such a contribution remains conditional on whether digital optimization produces meaningful changes in physical logistics activities rather than merely increasing processing speed, equipment density, or order throughput. During the development of the assessment framework, the relationship between automation and environmental performance initially appeared relatively straightforward; however, attempts to compare operational energy, vehicle movement, packaging use, computational demand, and equipment replacement within a common analytical boundary revealed several difficulties, particularly because reductions in impact intensity could coexist with increases in absolute resource consumption. The framework was consequently adjusted to distinguish physical and digital inventories, direct and indirect effects, and efficiency improvements from possible rebound effects. This adjustment did not remove uncertainty, but it made the underlying assumptions more visible. A decline in electricity use per order, for example, could indicate more efficient equipment control, yet it might also result from increased throughput spreading a largely fixed energy load across more orders, seasonal differences in heating or cooling demand, changes in product characteristics, or the exclusion of cloud-computing energy from facility records. Similar ambiguity applies to transportation indicators: fewer vehicle-kilometres per order may reflect better routing and consolidation, but the same pattern could emerge from reduced service coverage, relaxed delivery requirements, or the selective exclusion of remote destinations. An increase in distance, by contrast, might accompany improved rural accessibility, fewer failed deliveries, or the use of smaller low-emission vehicles. These alternative explanations indicate that environmental performance cannot be interpreted credibly through a single indicator, and that absolute consumption, normalized intensity, service quality, spatial coverage, resilience, and life-cycle impacts should be considered together. From a theoretical perspective, intelligent logistics automation may be more appropriately understood as a coupled cyber-physical and organizational system in which algorithms influence material movement while simultaneously generating their own energy, hardware, data-governance, and institutional requirements. This perspective shifts attention

away from the narrow question of whether automation is environmentally beneficial and toward the more demanding question of which combinations of technologies, operating rules, energy systems, organizational capabilities, and market conditions might allow environmental benefits to persist over time. For practitioners, the findings imply that environmental objectives should be defined before technologies are purchased and should be translated into measurable procurement, operation, maintenance, repairability, and end-of-life requirements. Reporting both absolute and intensity-based indicators may reduce the possibility that rapidly expanding logistics activity is presented as sustainable merely because the environmental burden per order has declined. The illustrative calculations used in this study remain transparent and reproducible, but they are not substitutes for enterprise-level measurements, and their results may change considerably when different electricity emission factors, equipment lifetimes, utilization rates, delivery promises, or system boundaries are adopted. Further research is needed to examine these relationships through matched before-and-after studies, longer-term field observations, life-cycle assessment of automation equipment and batteries, and operational experiments in which environmental constraints are incorporated directly into routing, scheduling, and resource-allocation decisions. Research might also explore carbon-aware edge computing, shared charging infrastructure, interoperable regional logistics platforms, the environmental consequences of system failure and recovery, and the distribution of benefits and burdens among enterprises, workers, consumers, and nearby communities. Considering the above factors, the broader significance of intelligent logistics automation may not lie simply in replacing manual activities with machines, but in making previously fragmented relationships among energy, materials, mobility, information, responsibility, and service expectations more measurable and potentially more governable. Its environmental value is unlikely to be uniform or automatic; nevertheless, when regional coordination, adaptive operation, circular resource management, resilient digital infrastructure, transparent measurement, and meaningful human oversight develop together, intelligent automation could, to some extent, support a transition toward logistics systems that are not only more efficient but also more accountable, adaptable, and environmentally responsible.

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ABOUT THE AUTHORS

LIN, Shengtao

Shenzhen Haitaobe Network Technology Co., Ltd,
CN, 15603059324@139.com.

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