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An Integrated Production-Distribution Planning in Green Supply Chain: A multi-objective evolutionary approach

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Abstract

The goal of this research is to develop a novel multi-objective mathematical model in a green supply chain network consisting of manufacturers, distribution centers and dealers in an automotive manufacture case study. The main objectives considered are: minimizing the costs of production, distribution, holding and shortage cost at dealers as well as minimizing environmental impact of logistic network. In addition to minimizing the costs and environmental impacts particularly the emission of CO_2, the model can determine the green economic production quantity using Just-In-Time logistics. Furthermore, multi-objective genetic algorithm is applied in order to minimize these two conflicting objectives simultaneously. Finally, the performance of the proposed model is evaluated by comparing the obtained Pareto fronts from MOGA and goal attainment programing solver in Matlab.

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Keywords: Green supply chain network, Integrated production-distrbution, Multi-objective optimization, Genetic algorithm, JIT;

1. Introduction

Since 1990s, green concerns have been gradually more considered in design and planning problems of both micro and macro levels by governments, people, industries and researchers. In the literature of supply chain management (SCM), green supply chain management (GSCM) lies in various ranges from green purchasing to integrated green supply chains through raw material suppliers to manufacturers to end users, and reverse logistics. Kumar [1] defined GSCM as environmental thinking integration into SCM, consist of design of product, sourcing and selecting of material, manufacturing processes, final product delivery to the customers along with end-of-life management of the product after its beneficial life. Therefore, the goals concern in GSCM are not only the economic impact of logistics policies on the organizations, but also inclusive impact on the earth, such as the effects on the environmental pollution, fuel consumption or hazardous waste.

Logistics is one of supply chain (SC) aspects which is the process of planning, implementing and controlling the flow and storage of goods or services. Logistics activities which form the main part of SCM-related processes is one of the leading environmental pollution sources and greenhouse emissions which may cause harmful impacts both on human health and quality of the ecosystem. Transportation and industrial processes have been linked to an increase in the greenhouse gas effect through carbon dioxide (CO_2) emissions, although the effect of other gases should not be under-estimated [2]. In the United States, for instance, CO_2 is the predominant greenhouse gas emitted, which accounts for 85% of the climate change potential for all human produced emissions. Emissions from trucks increased from 42% of total transportation CO_2 emissions in 1995 to 49% in 2006 and show no signs of decreasing [3].

However, the current competitive global markets have forced manufacturers to respond the customers' needs quickly with lower price and shorter delivery lead-time. So to be more flexible, responsive and to reduce operations cost,

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manufacturers try to apply various kinds of strategies. JIT strategy, for instance, is one of these them, which has been demonstrated to increase productivity of the companies through a substantial reduction of work-in-process inventory by frequent feeding of production inputs [16]. The small size, more frequent and premium shipments demand seem to cause higher environmental pollution, increase transportation cost and trading off inventory reduction versus higher environmental impacts. Transportation costs become a critical issue for total cost minimization. Consequently, companies should invest in design and planning to optimize their logistic network, while accounting for the trade-off between cost and environmental effects in this evaluation.

The concentration of classic mathematical production and distribution models are on total costs minimization subject to operational constraints while environmental impacts are not addressed. To cope with these conflicting objectives, we developed a multi-objective mathematical model within a supply chain network using JIT logistics. The objectives of the proposed model are to minimize the costs of production, distribution and holding as well as minimizing carbon emission in the whole logistics network. In addition, the model can determine the green economic production quantity (GEPQ) and dealers shortages. Later, a multi-objective genetic algorithm (MOGA) has been applied to solve the formulated mixed-integer linear problem.

This paper is structured as follows. Section 2 investigates relevant literature in the area of JIT and GSCN modeling. Section 3 defined the problem more precisely and mathematical formulation for the proposed model is explained. In Section 4, the proposed MOGA is presented in details. Computational results and discussion is described in Section 5. Finally, in Section 6, some areas of further research and conclusions are presented.

2. Literature Review

Evaluation of the environmental impact on different production and distribution strategies is one of the main green logistics (GLs) objectives that reduce the energy consumption of related activities in logistics. Although the GLs interest has grown since the last decades, however the current practice of logistics still rarely complies with environmental issues in JIT logistics.

Shyur and Shih [4] presented a multi criteria decision making (MCDM) model in the propose of applying JIT to delivery, production quality, price/cost, facilities, technology, response to customer needs, and exit quality criteria. Memari et al. [5] proposed a decision support system for a hybrid MRP/JIT supply network by using bi-level non-linear optimization model. Furthermore, Farahani and Elahipanah [6] developed multi objective mathematical model for a JIT distribution problem in a three-echelon distribution network in a supply chain. However, environmental impacts are not addressed in all traditional mathematical modeling. With green perspective, Tsai [7] conducted a fuzzy goal programming approach for green supply chain optimization. In the proposed approach, performance evaluation in value-chain structure and the well-known activity-based costing (ABC) are integrated aiming to find the optimal supplier selection and flow allocation. A multi-objective mixed-integer fuzzy mathematical model was proposed by Özceylan and Paksoy [8] for optimizing an integrated forward and reverse closed-loop supply chain network with multiple period and multiple items. A multi-objective fuzzy mathematical programming model was developed by Pishvaee and Razmi [9] for designing an environmental supply chain. Moreover, Pishvaee et al. [10] presented a bi-objective credibility-based fuzzy mathematical programming model for designing a GSCN. The model aims to make a trade-off between two conflicting objectives, i.e., minimization of total costs and minimization of the environmental impacts by defining CO_2 equivalent index in order to quantify the environmental burden of logistics activities. Mousazadeh et al. [11] proposed a multi-objective mathematical model to design a green and reverse logistics under fuzziness. In their study, they identified importance and drivers of the green logistics as well. Vahdani et al. [12] suggested a possibilistic-queuing model for designing a reliable closed-loop supply chain network. The model address total costs minimization and the expected transportation costs after failure of bidirectional facilities of the concerned network.

Among mathematical modeling literatures in the area of GLs, majority of previous studies applied conventional methods as a solution methodology due to their vast applications and simplicity. However, many of real-world cases belong to class of NP-hard problems and in order to solve NP-hard problems, evolutionary algorithms such as genetic algorithm (GA), is an efficient alternative. As a result, considering complexity of GLs objectives and constraints will lead to new problems that subsequently result in novel combinatorial optimization models which needs to be solved by an efficient heuristics/meta-heuristics.

3. Mathematical Modeling

The proposed model is divided into three levels: level 1 indicates the manufacturers, level 2 represents the distributors and level 3 denotes the dealers. In developing the proposed model the following assumptions and limitations were established: (1) The model is designed for multiple manufacturers, distributors, dealers, products and multi-periods. (2) The amount of demand was assigned to the manufacturers at the beginning of the period. (3) The locations of plants, distributors, dealers are fixed. (4) The capacities of the manufacturers, the distributors and the dealers are known. (5) The duration of each period was equal to the sum of the production time. (6) There is no inventory at the distributors at the beginning or end of the planning horizon. (7) Products are temporarily stored at the distributors before delivery to the dealers. (8) Transportation mode is only handled by trucks with fixed capacity for each type of products. (9) Dealers shortage is allowed and finally. In addition, several limitations were considered in the proposed model: I. All demands must be satisfied during the planning horizon. II. The production time is limited. III. The storage capacities for each perfect product are limited. IV. The capacities of the manufacturer, distributor and dealers are limited. V. The storage capacities for each perfect product are limited. The parameters and decision variables of the model are listed as follow:

Parameters

Γ_{jpt} Holding cost of products p at distributor j in period t.
ρ_{ipt} Production cost per item p by manufacturer i in period t.
υ_{ijpt} Shipping cost of each product p from manufacturer i to distributor j during period t.
$\ddot{\upsilon}_{jkpt}$ Shipping cost of each product p from DC j to dealers k during period t.
θ_{ipt} Time required to produce product p by manufacturer i in period t.
$T\theta_t$ Total production time during period t.
In_{pjt} Inventory of product p at distributor j during period t.
D_{kpt} Demand of dealer k for product p during period t.
Ca_{ipt} Production capacity of manufacturer i for product p in period t.
V_{jt} Total storage capacity of distributor j during period t.
V_{jpt} Storage capacity of DC j for product p in period t.
U_{kpt} Storage capacity of dealer k for product p in period t.
U_{kt} Total storage capacity of dealer k during period t.
S_{kpt} Shortage cost for each product p at dealer k during period t.
a_p The penalty cost of early/tardy deliveries per unit of product p.
$CO2_{ijpt}$ unit CO_2 emission per product p from manufacturer i to DC j during period t.
$CO2'_{jkpt}$ unit CO_2 emission per product p from DC j to dealer k during period t.

Decision Variables

α_{ijpt} Amount of products p transported from manufacturer i to distributor j during period t.
β_{jkpt} Amount of products p transported from distributor j to dealer k during period t.
χ_{ipt} GEPQ of products p by manufacturer i during period t.
γ_{kpt} Amount of shortage of products p in dealer k during period t.
ζ_{pt} Amount of products p which are not deliver on-time in period t in whole network.

$$MinZ1=\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{t=1}^{T}\rho_{ipt}.\chi_{ipt} +\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}\Gamma_{jpt}.\left(\sum_{\tau=1}^{t}\sum_{i=1}^{I}\alpha_{ijpt}-\sum_{\tau=1}^{t}\sum_{j=1}^{J}\beta_{jkpt}\right)+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}\upsilon_{ijpt}.\alpha_{ijpt}+\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T}\ddot{\upsilon}_{jkpt}.\beta_{jkpt}+\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T}S_{kpt}.\gamma_{kpt}+\sum_{p=1}^{P}\sum_{t=1}^{T}\zeta_{pt}.a_p \quad (1)$$

Eq.(1) denotes the first objective function that minimizes the total costs of the supply chain, including the costs of production, holding at the distributor, transportation from the manufacturers to the distributors, transportation from the distributors to the dealers and dealer shortages due to out of stock situations. In addition, penalty costs are considered for the amount of products not delivered on time (early or tardy deliveries) to ensure JIT deliveries.

$$MinZ2=\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{t=1}^{T}CO2_{ijpt}.\alpha_{ijpt}+\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{p=1}^{P}\sum_{t=1}^{T}CO2'_{jkpt}.\beta_{jkpt} \quad (2)$$

Eq. (2) states the second objective function that minimizes total carbon emission in whole logistics network. Note that for calculating carbon emissions, several methodologies have been applied (EcoTransIT [15], ARTEMIS [14], Greenhouse Gas protocol [13], etc.). Since Greenhouse Gas protocol is the most applied because of its easy application and worldwide scope, we also adopted this methodology in this research. The equivalent carbon emission per product can be calculated as a linear function that depends on the travelling distance (in kilometers) and the carried vehicle carbon emission (in grams of CO_2 per kilometer). We applied this carbon emission model for a given supplying mode and the carbon emission is proportional to the number of product units that are shipped.

$$s.t: \chi_{ipt}\le Ca_{ipt} \qquad \forall i,p,t \quad (3)$$

Eq. (3) states the limitation of production capacity.

$$\sum_{i=1}^{I}\sum_{p=1}^{P}\alpha_{ijpt}\le V_{jt} \qquad \forall j,t \quad (4)$$

$$\sum_{i=1}^{I}\alpha_{ijpt}\le V_{jpt} \qquad \forall j,p,t \quad (5)$$

Eqs. (4) and (5) denote the distributors delivery capacity restrictions for each type of product and all types of products, respectively.

$$\sum_{j=1}^{J}\sum_{p=1}^{P}\beta_{jkpt}\le U_{kt} \qquad \forall k,t \quad (6)$$

$$\sum_{j=1}^{J}\beta_{jkpt}\le U_{kpt} \qquad \forall k,t \quad (7)$$

Eqs. (6) and (7) indicate the limitations of delivery capacity for the dealers for each type of product and all types of products, respectively.

$$\sum_{k=1}^{K}D_{kpt}\le \chi_{ipt} \qquad \forall p,t \quad (8)$$

Eq. (8) considers that total production is equal to the sum of demand.

$$\sum_{k=1}^{K}\gamma_{kpt}=\sum_{k=1}^{K}D_{kpt}-\sum_{k=1}^{K}\chi_{ipt} \qquad \forall p,t \quad (9)$$

Eq. (9) investigates the amounts of shortage at the dealers.

$$\sum_{j=1}^{J} \beta_{jkpt} = D_{kpt} \qquad \forall k, p, t \tag{10}$$

Eq. (10) clarifies how the total demands in the planning horizon are supplied.

$$\sum_{k=1}^{K}\sum_{\tau=1}^{t} \beta_{jkp\tau} \le \sum_{i=1}^{I}\sum_{\tau=1}^{t} \alpha_{ijp\tau} \qquad \forall j, p, t \neq T \tag{11}$$

$$\sum_{j=1}^{J}\sum_{p=1}^{P} \beta_{jkpt} = \sum_{i=1}^{I}\sum_{p=1}^{P} \alpha_{ijpt} \qquad \forall j, p \tag{12}$$

Eqs. (11) and (12) show the inventory at the distributors; note that there is no inventory in the beginning and at the end of the planning horizon at each distributors.

$$\sum_{i=1}^{I}\sum_{\tau=1}^{t} \alpha_{ijp\tau} - \sum_{k=1}^{K}\sum_{\tau=1}^{t} \beta_{jkp\tau} = In_{pj\tau} \quad \forall j, p, t \neq T \tag{13}$$

Eq. (13) represents the balance between the total inputs and outputs of goods moving to and from the distributors during the planning horizon.

$$\sum_{i=1}^{I}\sum_{p=1}^{L} \theta_{ipt} . \chi_{ipt} \quad \le T\theta_t \qquad \forall t \tag{14}$$

Eq. (14) illustrates the available time limitations of the production facilities for all production processes.

$$\alpha_{ijpt}, \beta_{jkpt}, \chi_{ipt}, \gamma_{kpt} \ge 0, integer. \quad \forall i, j, k, p, t \tag{15}$$

Eq. (15) ensures non-negativity values of the production amount, deliveries to warehouses and dealers and dealer shortages.

4. Multi-Objective Genetic Algorithm

Genetic operators and representations applied in multi-objective optimization of SCN are described in this section. Firstly, a certain number of chromosomes are randomly generated as an initial population. Then each individual fitness is subsequently evaluated. The individuals are sorted based on their fitness, and after crossover and mutation operations, the parents and produced children are placed in the pool. The objective function value of the children is calculated. Lastly, the next generation of chromosomes is selected among these chromosomes based on the population size and the procedure continues until the maximum generation that usually defined as the stopping criteria. The chromosomes are arranged according to the objective function value and the best chromosomes are selected for producing the next generation.

4.1. Generating initial population

A certain number of chromosomes were randomly created according to Eq.(1) and Eq.(10). The amount χ_{ipt} should be expressed as follows:

$$\sum_{k=1}^{K} D_{kpt} < \sum_{i=1}^{I} \chi_{ipt} \le \sum_{i=1}^{I} Ca_{ipt} \qquad \forall I, t \tag{16}$$

4.2. Chromosome

One of the key components of the GA is the selection of chromosomes. In the developed mathematical model, the variable χ_{ipt} has both direct and indirect relationships with the variables α_{ijpt}, β_{jkpt}, γ_{kpt}. Thus, any change in variable χ_{ipt} leads to certain changes in other variables, and therefore, the variable χ_{ipt} was selected as the chromosome.

4.3. Non-dominated sorting

After evaluation of chromosomes, according to the concept of Pareto optimality and based on the values of Z1 and Z2, they are sorted accordingly. All non-dominated chromosomes are ranked in the first level and are given the same arbitrary large value as a fitness value. Then, without considering the chromosomes in the first level, among the remaining chromosomes, the non-dominated ones will be ranked in a lower level. This process continues as long as all chromosomes are sorted. The fitness values decrease as we go down the levels.

4.4. Elitism

The parents are defined as the chromosomes which ranked in the first level, and they are copied to the mating pool. The remaining parents are identified based on one of the roulette wheel, tournament selection, uniform and other approaches.

4.5. Selection of parents

The binary tournament method is applied in order to select the remaining parents. Then, they are copied into the mating pool. If the chromosomes number in first-level is equal to elite number, the process will be repeated a number of times. In every stage, the greater fitness value obtained from two random chromosomes is copied into the mating.

4.6. Crossover

To perform the crossover, two chromosomes must be merged. First, the chromosomes to be combined should be identified and allowed to mix. The columns will be combined for each chromosome selected for the crossover, and the intersection point will be used to combine the chromosomes. In this study, firstly, we chose the intersection point. Afterward, both side values of the matrix are exchanged. The crossover probability is set at 0.4.

4.7. Mutation

The mutation probability refers to the probability of change in any gene. In this study, each chromosome receives a certain number of genes that are assumed to change, and this number is derived by multiplying the total number of genes by the mutation probability. Accordingly, a number of genes must be selected to undergo mutation. For example, if the mutation probability is 0.4 and I = 2, L = 3, and T = 4, the total number of genes required to undergo mutation will calculated as follows: Round (0.4 * 2 * 3 * 4 = 9.6) = 9. The resulting value is rounded off to the nearest whole number. Thus, in this example, three genes should undergo mutation. These three genes are randomly selected, and their values are changed. We consider the rate of 0.3 as the mutation probability.

4.8. Selecting the new generation

To select chromosomes for the next generation, feasible chromosomes have to compete; therefore, the chromosomes population size for entering the next generation can be selected. In the mating pool, if the total feasible chromosome number is greater than population size, non-dominated sorting procedure is used to sort them. In the next step, fitness value for each one is determined and the fittest one is selected as population size of chromosomes. If the total number of feasible chromosomes in the mating pool is equal to population size, all the chromosomes will enter the next generation. To end, if the total feasible chromosome number is less than population size, then the following procedure will be done. In a nutshell, in the first step, the feasible chromosomes are sorted, and their fitness values are calculated. Afterward, feasible chromosome is determined as the nearest integer equal to or less than the feasible chromosome number, by which population size is divisible. Then, feasible chromosomes of the fittest one are selected, and for next generation, feasible chromosomes population size of each of them enter the next generation. This, in total, will add up to population size chromosomes into the pool. The fittest chromosomes are recorded at the end, for each generation.

4.9. Reporting

To end the algorithm, the termination conditions should be reached. The termination conditions are: the algorithm repeats for maximum generation number of times, for all generations, among the fittest chromosomes, non-dominated ones are identified and reported as the problem solutions. Fig.1 illustrates the flowchart for MOO used in this study.

5. Results and Discussion

5.1. Numerical experiments

Our numerical experiments utilize data that we obtained from the project with one of Malaysian automaker with slightly modifications. The following is the detailed list of the data:

- Two vehicle models (p =2), two manufacturing plants (i =2), five car dealers (k =5) and two DCs (j =1). The transportation costs are: υ_{ijpt} = Normal (8,3) and $\hat{\upsilon}_{jkpt}$= Normal (12, 5).
- Other costs include unit production costs ρ_{ipt} = Uniform (2, 100), unit holding cost Γ_{jpt} = Normal (10, 3) and unit shortage cost Normal (10, 2).
- With two daily shifts and 8 hours per shift, daily production is 180 vehicles per model. We considered 4 weeks of production and there is 5 working days per week.

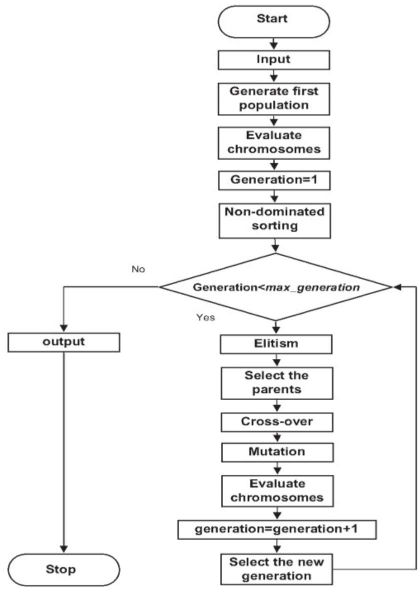

Fig. 1. Multi-objective genetic algorithm [6]

The weekly demand for vehicles is distributed normally with Normal (920, 40).

- The transportation mode only use road transport with trucks (truck capacity = 6). We assume all trucks year model are between 2005-peresent and carbon emissions are calculated based on amount of gasoline consumed per traveling distance (kilometer) based on Greenhouse Gas protocol [13].

Numerical experiments show that integrating environmental issues is not the only matters; it is also a good business sense and more profitable. With JIT perspective, it can provide a balance among transportation frequency, total costs as well as environmental impact. The results show that reduction in the amount of carbon emissions will lead to reduced costs because the environmental-based objective function has a tendency towards using less air polluted distribution. The cost-based objective function offers optimum number of transportation trips which will also give a positive environmental impacts. Finally, the decision maker, based on the company's preference, sets minimum acceptable feasible solution.

5.2. Performance evaluation of the algorithm

In order to validate and evaluate the performance of the proposed model, Pareto front obtained from MOGA is compared with the Pareto front resulting from goal attainment optimization solver in Matlab 7.13.0 software. Comparison between the results of the MOGA-II and goal attainment shows that the MOGA has better results for larger problem sizes. The studied MOGA was tested with different generation sizes. The appropriate generation size was 250; increasing the generation size increased the run-time of the MOGA but resulted in minimal changes in the results. In the proposed MOGA, the population size was set at 100. Therefore, in each generation, 100 non-dominated answers were produced, and the best solution of 100 answers was reported based on normalizing objective functions where they are summed together with a weight of 0.5 each together with the best answer in each generation. Additionally, to demonstrate the performance accuracy of the proposed model, each sample problem was solved five times by MOGA and goal attainment solver in Matlab.

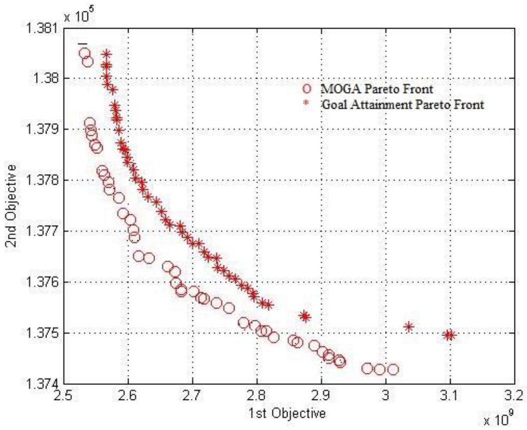

Fig. 2. An example of Pareto fronts of the proposed solutions.

The computational results for each run and for both objective functions are shown in Table 1. Note that the obtained results for Z1 and Z2 is the average of non-dominated answers for each run.

Table 1. Computational experiments for five runs of the proposed solutions.

Run No.	MOGA Results		Goal Attainment Results		| Gap between methods |	
	Z1(min)	Z2(min)	Z1(min)	Z2(min)	Z1	Z2
1	2.612E+09	1.375E+05	2.691E+09	1.378E+05	0.79E+09	0.003E+05
2	2.798E+09	1.374E+05	2.774E+09	1.376E+05	0.024E+09	0.001E+05
3	3.006E+09	1.305E+05	3.002E+09	1.375E+05	0.004E+09	0.070E+05
4	2.514E+09	1.379E+05	2.561E+09	1.380E+05	0.047E+09	0.001E+05
5	2.859E+09	1.375E+05	3.974E+09	1.3751E+05	0.115E+09	0.0001E+05

6. Conclusion

This study proposes a novel mathematical model for optimizing supply chain costs with respect to environmental impact. The aim of the model is to optimize total costs, including production, holding, shipping, and dealer shortages due to out of stock as well as minimizing carbon emission in the whole logistics system. Furthermore, this model can be applied as a decision support system in order to determine the green economic production quantity (GEPQ). MOGA and goal attainment techniques were used to solve the proposed mathematical model. The calculated gap between the best results of the MOGA and goal attainment solver demonstrates the accuracy and fine function of the proposed model.

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