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LOW-CARBON PRODUCTION CONTROL AND RESOURCE ALLOCATION OPTIMIZATION

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Abstract
The existing simulation platforms cannot effectively simulate large-scale low-carbon production control systems. To solve the problem, this paper explores the low-carbon production control and resource allocation optimization based on dynamic integrated simulation. Firstly, a multi-level integrated simulation architecture was provided for low-carbon production control, and the core functional modules were introduced in detail. Next, a resource allocation optimization model was constructed under carbon emissions policies. Drawing on the business flows on different levels in different production phases, the authors investigated how to build a simulation model for the process information of low-carbon production, and the multi-resolution basic information of production resources. In addition, the integrated simulation flow was explained fully for the proposed model. The effectiveness of our model was verified through experiments.
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Key Words: Integrated Simulation, Low-Carbon Production, Production Control, Resource Allocation

1. INTRODUCTION

At present, the resource-and technical-intensive manufacturing industry calls for high-quality control of the production process [1-9]. To ensure the safety and stability of modern manufacturing, it is necessary to effectively integrate production resources, production and transportation, production information flow, as well as the manpower and funds invested in production [10-15]. With the deterioration of the eco-environment, energy saving and emission reduction becomes mandatory for the development of manufacturing [16-19]. It is urgent for enterprises to develop new theories and techniques for sustainable manufacturing. Many scholars have laid stress on how to improve corporate energy efficiency, and reduce carbon emissions [20-24]. However, most of the simulation software in the relevant fields is utilized independently, and the simulation models have a poor integration capacity. Thus, deeper research is needed to realize the job shop-level integrated modelling and simulation for modern industrial manufacturers.

The emergence of Industry 4.0 has accelerated the digitalization of industrial scenarios. The integrated simulation system attracts broad attention, as a novel empowering technique, and a special decision support tool. Guizzi et al. [25] defined an integrated parameterized simulation model to enhance integrated management of production and maintenance processes, and developed a realization framework for simulation models, which help production and maintenance managers make economic and efficient decisions, and optimize the utilization of resources.

Modelling and simulation are important means to support the analysis and development of complex products. The whole-process, full-system modelling and simulation often need the collaboration between the system modelling language and the multi-physical modelling language and simulation platform. Nakamura et al. [26] proposed the X language, a new language for intelligent integrated modelling and simulation, to support the illustration of the structure and physical behaviour of system layers, as well as the construction of complex agent models.

The traditional production planning model does not involve the constraints of process operations. To optimize the production plan of refineries, and ensure the unit operating conditions in the optimal plan, Dong et al. [27] optimized and integrated the production plan and process operation of the petrochemical industry, and obtained the operating conditions by optimizing the production plan on process simulation software. Taking a refinery as the example, Dong et al. proved that their approach guarantees the accessibility of the production plan. The optimization improves the practical application of the production plan.

The design and development of complex products are a multi-disciplinary collaborative process that requires distributed teamwork. However, traditional simulation methods discipline-specific. In distributed collaborative environments, the existing simulation models cannot be shared and reused efficiently. To solve the problem, Yu et al. [28] designed a multi-level knowledge framework for knowledge representation, retrieving, and reasoning of simulation models. The Web service technology was adopted to share simulation knowledge, and an engineering application model was prepared to encapsulate simulation knowledge in an integrated manner. This model contains the information about geometric models, design algorithms or analysis codes.

The current integrated simulation platforms cannot reflect the standards or protocols adopted by low-carbon production control systems. The poor expansibility and weak flexibility make it impossible to carry out largescale simulations on the platforms. Therefore, this paper explores the low-carbon production control and resource allocation optimization based on dynamic integrated simulation. Firstly, Section 2 provides a multi-level integrated simulation architecture for low-carbon production control, and introduces the core functional modules, including simulation module for the supply chain on the planning layer, simulation module for the scheduling layer, whole-process simulation module for process control, and simulation module for dynamic flow of key equipment. Before simulation, Section 3 constructs a resource allocation optimization model under carbon emissions policies. Targeting traditional manufacturers, Section 4 considers the business flows on different levels in different production phases, discusses how to build a simulation model for the process information of low-carbon production, and the multi-resolution basic information of production resources, and details the integrated simulation flow for the proposed model. The effectiveness of our model was verified through experiments.

2. MULTI-LEVEL INTEGRATED SIMULATION ARCHITECTURE

The multi-level integrated simulation architecture for low-carbon production control consists of multiple modules, namely, simulation module for the supply chain on the planning layer, simulation module for the scheduling layer, whole-process simulation module for process control, and simulation module for dynamic flow of key equipment. The parameters of each functional module should be properly configured, and the different modules must interact with each other appropriately. Fig. 1 shows the relationship between the functional modules. A slight change to a functional module may affect the execution of all the other modules, and in turn cause the entire production control system to behave differently. The consequences of any change of any module are immense.

A possible way to discuss each functional module is to evaluate each module through simulation, and verify the reasonability of the hypotheses made before the simulation. The performance of the entire production control system depends on the interaction between functional modules. Therefore, it is of pivotal importance to evaluate the interactivity between these modules during the simulation. Hence, the four simulation modules, namely, simulation module for the supply chain on the planning layer, simulation module for the scheduling layer, whole-process simulation module for process control, and simulation module for dynamic flow of key equipment, need to be debugged independently, before being integrated for centralized debugging.

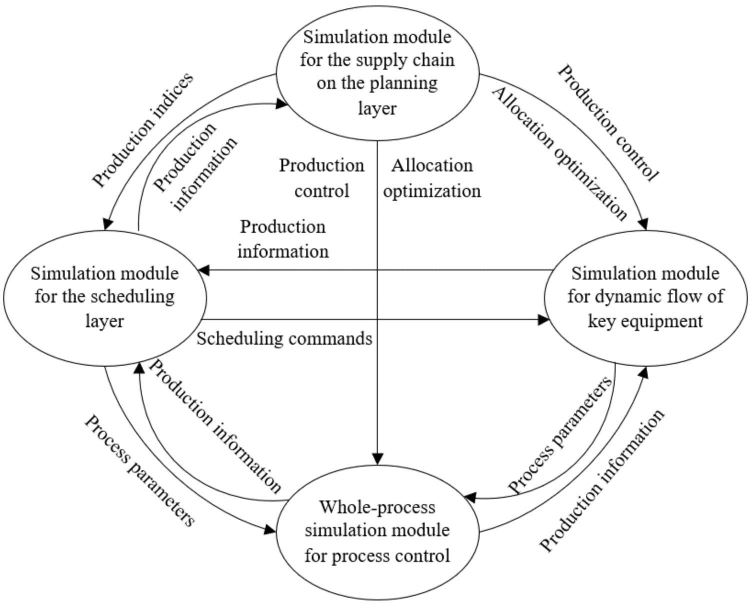

Figure 1: Relationship between functional modules.

Based on market supply and demand, the simulation module for the supply chain on the planning layer can predict many issues, such as the price and supply of raw materials, the price and demand of products, the transportation capacity of raw materials and products, the production capacity of the job-shop, the inventory capacity of the producer, and simulate the position and state changes of raw materials and products in each link of the supply chain. In addition, this module can emulate the random oscillation of uncertain disturbances.

The simulation module for the scheduling layer can simulate the production process under low-carbon constraint, including the start and stop of production equipment, production plan, cyclic processing plan, as well as the transformation, delivery, and storage of raw materials, parts, and products. The module can also predict the occurrence of production equipment failures.

Referring to the production techniques, detailed standard production data, and empirical models, the whole-process simulation module for process control can simulate how the production rate is affected by raw material supply, parts properties, and equipment operating conditions in the production process. Moreover, the module can track the stats of raw materials, parts, and products, and predict carbon emissions.

Based on strict production and control principles, the simulation module for dynamic flow of key equipment can establish precise models for the techniques and control of key production equipment, simulate all possible operations under regular working conditions, analyse the dynamic responses of equipment to the changes in operating conditions, production demand, or raw material/parts supply, laying the basis for the dynamic stability of the equipment.

Apart from the construction of key simulation modules, the greatest challenge to the multi-level integrated simulation of low-carbon production control is to simulate numerous production control and resource allocation nodes. As the number of nodes increases, the computer memory and processor resources required for simulation grow linearly. During the wireless network simulation of large-scale production sites, each functional module needs to compute all adjacent nodes in the communication range of the corresponding production control and resource allocation node, before judging whether an adjacent node receives the information from that node. Therefore, the resource consumption is proportional to the square of the number of nodes. For large-scale production sites, it is often necessary to model and simulate more than 10,000 nodes. Only multi-level integrated simulation systems can complete the simulation task.

3. RESOURCE ALLOCATION OPTIMIZATION MODEL

Prior to simulation, a resource allocation optimization model was established under carbon emissions policies. Without considering the effect of carbon emissions, the original simulation model was set up for production resource allocation. The model involves two decision variables, namely, a 0-1 decision variable, and a resource demand decision variable. The 0-1 decision variable $u_{ab\beta}$ represents the option of resource allocation:

$$u_{ab\beta} = \begin{cases} 1, & \text{if node } j \text{ of product } a \text{ selects resources } \beta \\ 0, & \text{otherwise} \end{cases} \quad \forall a, \forall b, \forall \beta \tag{1}$$

The resource demand decision variable $v_{gb\beta}$ represents the number of production resources β allocated from supplier g to the resource allocation node b:

$$v_{gb\beta} \geq 0 \quad \forall g, \forall b, \forall \beta \tag{2}$$

Let $t_{gb\beta}$ be the supply cost of the production resources β allocated from supplier g to the resource allocation node b. The proposed simulation model aims to minimize the resource supply cost. This cost can be calculated by:

$$E^C = \sum_{g=1}^{G} \sum_{b=1}^{B} \sum_{\beta=1}^{\Gamma_b} v_{gb\beta} t_{gb\beta} \tag{3}$$

The constraints are detailed below. The production resources to be allocated to the same machine must be selected by the principle of choosing one resource out of many:

$$\sum_{\beta=1}^{\Gamma_j} u_{ab\beta} = 1 \quad \forall a, \forall b \tag{4}$$

In low-carbon production control, the resources must be selected by the following rule:

$$u_{ab\beta} \leq u_{ab'\beta'} \qquad \forall a \forall \left(b_\beta, b'_{\beta'}\right) \in CHI \tag{5}$$

The incompatibility rule can be expressed as:

$$u_{ab\beta} + u_{ab'\beta'} \leq 1 \qquad \forall a \forall \left(b_\beta, b'_{\beta'}\right) \in NCHI \tag{6}$$

To ensure that the final allocation meets the requirements of production equipment, this paper describes whether a machine chooses the production resources supplied by a resource allocation node. The machine needs the resources, and does not need the resources can be respectively expressed as:

$$u_{ab\beta} = 1 \qquad \forall \left(a, b, \beta\right) \in NE \tag{7}$$

$$u_{ab\beta} = 0 \qquad \forall \left(a, b, \beta\right) \in NNE \tag{8}$$

To ensure that the production demand is sufficient for completing the production task, the production resources demanded by each resource allocation node must be equal to or greater than the production demand. Thus, the balance constraint of production resources can be expressed as:

$$\sum_{a=1}^{A} r_a p_a u_{ab\beta} = \sum_{g=1}^{G} v_{gb\beta} \qquad \forall b \forall \beta \tag{9}$$

Considering the supplier's limited supply capacity of production resources, the demand for production resources should be smaller than the maximum supply capacity of the supplier. The supplier's supply capacity of production resources must satisfy:

$$v_{gb\beta} \le b_{gb\beta} \qquad \forall g \forall b \forall \beta \tag{10}$$

Under carbon emissions policies, the total amount of carbon emitted by a job shop must be smaller than a pre-set fixed value called the carbon cap. Let o^{CEA} be the carbon cap; $o^{PCE}{}_{kb\beta}$ be the production carbon emission of production resources β at resource allocation node j; $o^{ACE}{}_{b\beta}$ be the carbon emissions of the assemblage. To limit the carbon emissions of the job shop in production control and resource allocation, the following constraint should be introduced to the simulation model:

$$\sum_{g=1}^{G}\sum_{j=1}^{J}\sum_{\beta=1}^{\Gamma_j}\left(v_{gb\beta}o_{b\beta}^{PCE}+v_{gb\beta}o_{gb\beta}^{ACE}\right)\le o^{CEA} \tag{11}$$

Under carbon emissions policies, the low-carbon production control and resource allocation optimization model can be expressed as:

$$\begin{aligned} &\text{Objective: } Min\ E^{C} \\ &\text{s.t.} \\ &\text{Constraints (4) – (11)} \\ &\quad u_{ab\beta}\in\{0,1\} \\ &\quad v_{gb\beta}\ge 0 \end{aligned} \tag{12}$$

Under carbon emissions policies, every unit of carbon dioxide emitted from the job shop will be taxed. Unlike the carbon cap, the carbon tax is not greatly correlated with the total carbon emissions of the job shop during the production. Let ζ be the carbon tax rate; υ be the penalty coefficient. Then, the objective function of the original simulation model under carbon emissions policies can be established as:

$$\min\sum_{g=1}^{G}\sum_{b=1}^{B}\sum_{\beta=1}^{\Gamma_b}v_{gb\beta}t_{gb\beta}+\zeta\upsilon\sum_{g=1}^{G}\sum_{b=1}^{B}\sum_{\beta=1}^{\Gamma_b}\left(v_{gb\beta}o_{b\beta}^{PCE}+v_{gb\beta}o_{gb\beta}^{ACE}\right) \tag{13}$$

Thus, the low-carbon production control and resource allocation optimization model under carbon emissions policies can be finalized as:

$$\begin{aligned} &\text{Objective: Eq. (12)} \\ &\text{s.t.} \\ &\text{Constraints (4) – (11)} \\ &\quad u_{ab\beta}\in\{0,1\} \\ &\quad v_{gb\beta}\ge 0 \end{aligned} \tag{14}$$

4. INTEGRATED SIMULATION FLOW

Based on the above optimization model and integrated simulation framework, this section considers the business flows on different levels in different production phases of traditional manufacturers, and discusses how to build a simulation model for the process information of low-carbon production, and the multi-resolution basic information of production resources.

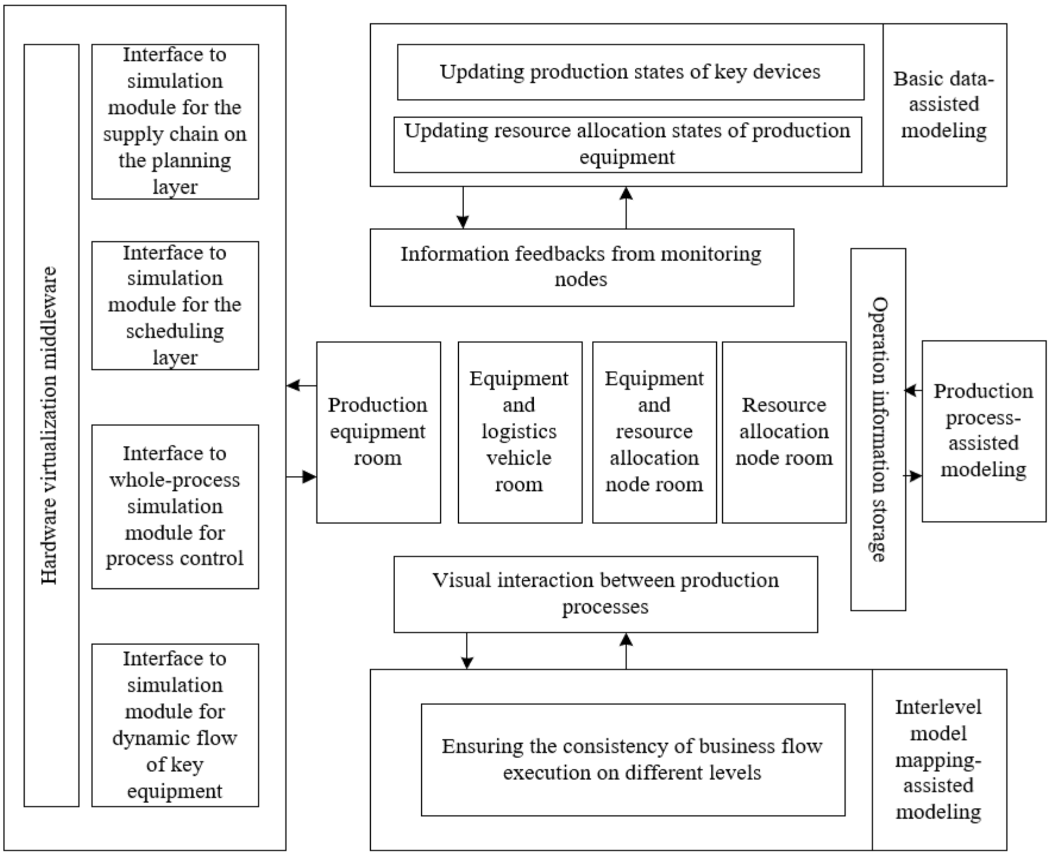

Figure 2: Structure of integrated simulation platform.

Fig. 2 shows the structure of the integrated simulation platform. The emulators corresponding to the functional modules are mainly responsible for simulating the issues related to low-carbon production control and resource allocation, such as warning of raw materials / parts supply and demand, completion time forecast, emergency equipment fault management, logistics navigation, carbon limit reminder, and emergency reminder light of production accidents.

The emulators work in the following manner: In the job-shop, the execution state of each monitoring node of low-carbon production control and resource allocation needs to be sent to the adjacent nodes, using the application programming interface (API) provided by the emulators of the wireless transmission network. Once an emulator detects that a node receives the monitoring information, it will notify the relevant nodes, and supervise them to complete the task of production control and resource allocation.

This proposed multilevel integrated simulation model synthetizes the emulators of the process information model of low-carbon production, with the emulators of the multi-resolution basic information model of production resources, to carry out the relevant simulation experiments.

The proposed multilevel integrated simulation model functions like a middleware. It provides an ideal virtual computing environment for the low-carbon production control and resource allocation in the job-shop, shields the heterogeneity between the proprietary software of the four simulation modules, and completes the following functions: production cycle management, time synchronization of the emulators of different functional modules, caching the information about production control and resource allocation, and optimal data transmission for the wireless communication of the production control system.

The production resources are allocated under the constraint of carbon emissions policies. From the angle of minimizing resource supply cost, numerous production control tasks are aggregated into a relatively stable and unified monitoring and transmission model for resource allocation information. In this way, the complexity of each functional module emulator is shielded, making it much easier to integrate the information about production control and resource allocation to each emulator.

The proposed multilevel integrated simulation model is responsible for coordinating the four functional modules, starting the emulator corresponding to each module, and synchronizing the time, state, and data interaction between all emulators.

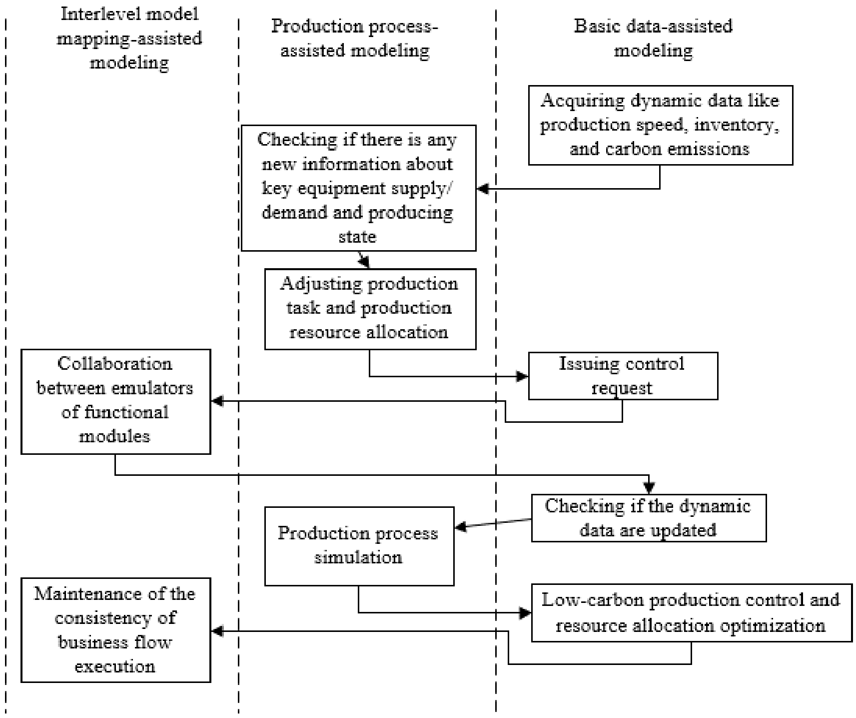

Figure 3: Workflow of our simulation model.

Table I: Actual allocation data for resource allocation optimization model under carbon emissions policies.

Key devices	**Operations**	**Resource supply cost**		**Delivery period**		**Carbon emissions**	
		***S*1**	***S*2**	***S*1**	***S*2**	***S*1**	***S*2**
A	A1	1285	1302	12	20	18.2	18
	A2	52.6	23.6	8	25	24.8	35
B	B1	145	112.7	15	16	65	22
	B2	128.2	75.2	13	19	11.2	26
	B3	118.4	45.1	18	22	48.5	52.4
C	C1	42.5	33.6	12	13	12.4	22.7
	C2	148.2	88.5	18	17	3.5	3.5
D	D1	98.5	71.2	13	21	12.7	22.8
	D2	76.2	28.4	7	26	20.8	41.5
	D3	61.8	18.2	8	18	3.16	55
E	E1	13.5	105.7	13	23	7.5	1.32
	E2	135.7	92.1	16	16	55.8	58.5
F	F1	11.2	65.7	22	20	57.4	62
	F2	152.6	88.4	9	15	25.8	33.7
	F3	118	78.3	6	13	40.2	4.35

The functional modules exchange data under the Transmission Control Protocol (TCP) / Internet Protocol (IP), which facilitates the connections between the emulators.

The multilevel integrated simulation model relies on the TCP/IP to connect the emulator of each functional module. At the start of simulation, the multilevel integrated simulation model starts the emulators of the four simulation modules, and kicks off cyclic simulations. The integrated simulation flow of our model is detailed as follows (Fig. 3):

(1) Executing the simulation time step of production process-assisted modelling

In a largescale production environment, the multi-resolution basic information model of production resources is adopted to simulate the message transmission between machines, between machines and logistics vehicles, between machines and resource allocation nodes, and between resource allocation nodes. The production process-assisted model returns the information sent by monitoring nodes (mainly the messages received synchronically by adjacent nodes) to the multilevel integrated simulation model. The multilevel integrated simulation model will realize the visual interactive operation of the whole process of the production flow. Finally, the operation information will be saved in the data storage unit corresponding to each monitoring node.

(2) Executing the simulation time step of basic data-assisted modelling

The basic data-assisted modelling can update the production states of key devices, including dynamic data like production speed, inventory, and carbon emissions, according to the updates of its business applications, namely, device management, quality management, and utility management. The resource allocation state of production equipment is updated by the solving algorithm to the resource allocation optimization model under carbon emissions policies. After completing its simulation time step, the basic data-assisted model will return the production equipment states and resource allocation states to the multilevel integrated simulation model. The multilevel integrated simulation model will update the stored basic data on production control and resource allocation, according to the returned information.

(3) Executing the simulation time step of interlevel model mapping-assisted modelling

To ensure the execution consistency between business flows on different levels, the same raw material or part is described in a unified manner by the same logic, according to the basic data on production control and resource allocation, which are obtained by the emulators of different functional modules. In the multi-resolution basic information model of production resources, the received and sent data collected by emulators are screened, such as to maintain the dynamic mapping of all information.

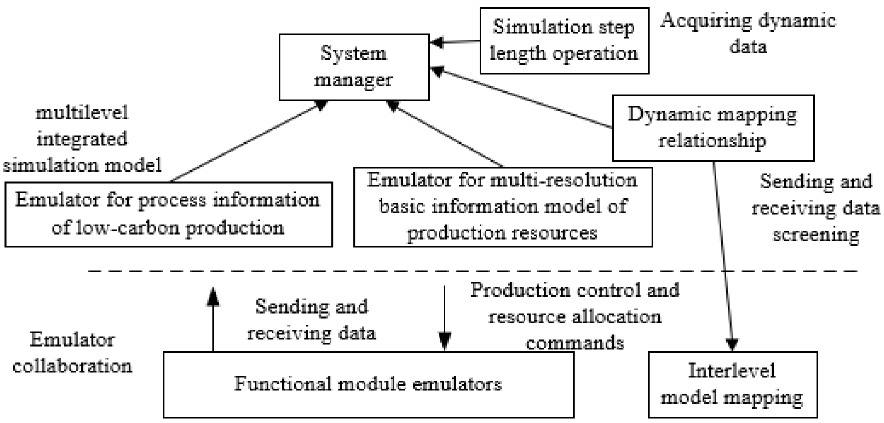

Figure 4: Application of multilevel integrated simulation model.

(4) Executing the simulation time step of multilevel integrated simulation model

Under the constraint of carbon emissions policies, the proposed application of the multilevel integrated simulation model will start the emulators for the process information model of low-carbon production, and the multi-resolution basic information model of production resources, adjust the production tasks, and change the allocation of production resources, upon receiving the supply, demand, and production state from key equipment. Fig. 4 illustrates the application of the multilevel integrated simulation model. In the proposed multilevel integrated simulation model, this process is completed through the collaboration between the emulators of functional modules.

5. EXPERIMENTS AND RESULTS ANALYSIS

Table I shows the key devices and production cases of a product of a manufacturer, plus the resource supply cost and carbon emissions of the cases. The carbon emissions of each operation on each key device was calculated by the proposed estimation method. Fig. 5 shows the curve between resource supply cost and carbon emissions under different carbon tax rates.

As shown in Fig. 5, the resource supply cost of the product increased, while the carbon emissions gradually dropped, with the carbon tax rate. Thus, carbon tax policies have a great impact on the carbon emissions of modern manufacturers. When the carbon tax rate is low, the enterprise would emit more carbon. During the operation, modern manufacturers tend to accept the carbon tax policies, for the policies do not directly impede corporate operation.

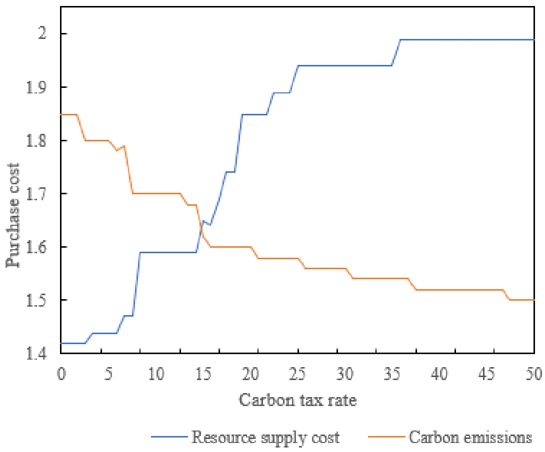

Figure 5: Influence of carbon tax rate on resource supply cost and carbon emissions.

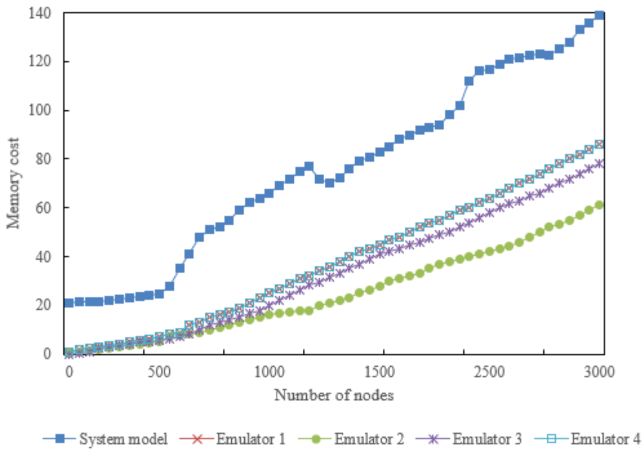

Figure 6: Relationship between the number of phases and memory cost.

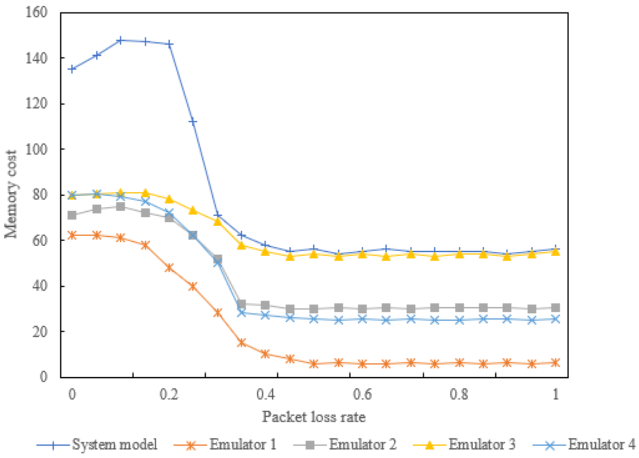

Figure 7: Relationship between the number of phases and packet loss rate.

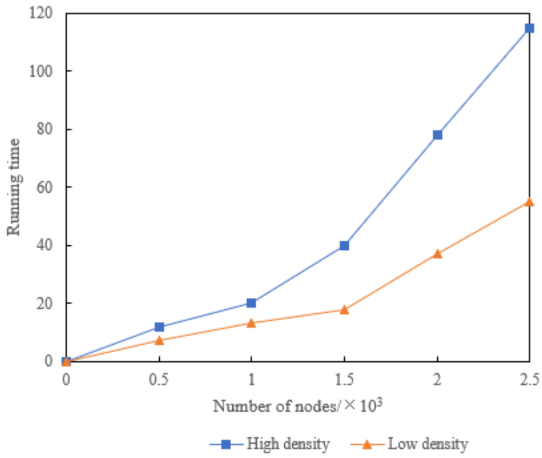

Figure 8: Relationship between node number and simulation time.

Figs. 6 and 7 display the relationship between the number of phases and memory cost, and that between the number of phases and packet loss rate. It can be observed that the model consumed a large memory, at different number of nodes, and different packet loss rates. Figs.

8 to 10 display the correlation of simulation time with the number of nodes, the physical layer model, and communication range, respectively. It is clear that the simulation time of our model increased with the rising density and number of nodes, the simplification of the physical layer, and the growing communication distance.

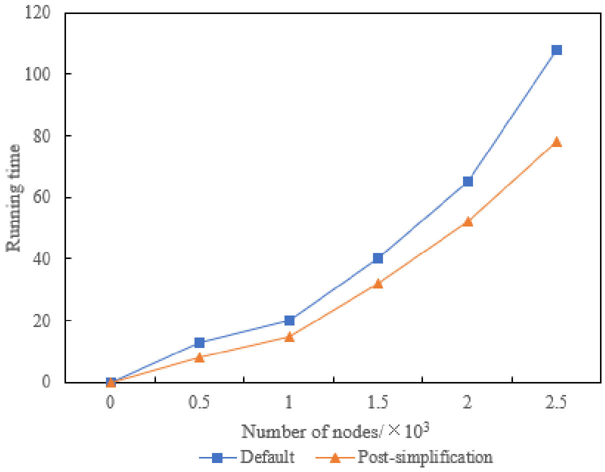

Figure 9: Relationship between physical layer model and simulation time.

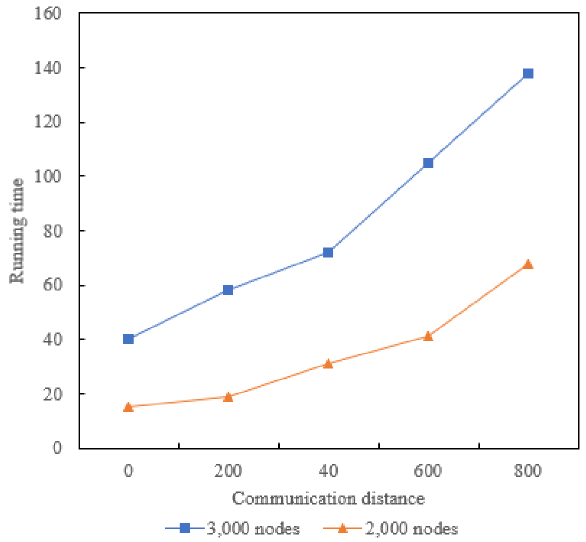

Figure 10: Relationship between communication range and simulation time.

The above analysis shows that the proposed multilevel integrated simulation model, which is based on the emulators of different functional modules, supports largescale simulation, achieves desirable performance, and realizes relatively high simulation accuracy.

6. CONCLUSIONS

Based on dynamic integrated simulation, this paper investigates the low-carbon production control and resource allocation optimization. After specifying the multi-level integrated simulation architecture for low-carbon production control, the authors detailed the core functional modules, and established a resource allocation optimization model under carbon emissions policies. The next is to build a simulation model for the process information of low-carbon production, and the multi-resolution basic information of production resources. In addition, the integrated simulation flow was explained fully for the proposed model. Through experiments, the actual allocation data were presented for the resource allocation optimization model under carbon emissions policies. Referring to these data, the authors analysed the influence of carbon tax rate over resource supply cost and carbon emissions. It is concluded that carbon tax policies have a great impact on the carbon emissions of modern manufacturers. Further, the authors plotted the curve between node number and memory cost, and that between packet loss rate and memory cost of different emulators for the multilevel integrated simulation model, and discussed the correlation of simulation time with the number of nodes, the physical layer model, and communication range. The results show that proposed multilevel integrated simulation model supports largescale simulation, achieves desirable performance, and realizes relatively high simulation accuracy.

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REFERENCES

[1] Bueno, A.; Filho, M. G.; Carvalho, J. V.; Callefi, M. (2022). Smart production planning and control model, Mesquita, A.; Abreu, A.; Carvalho, J. V. (Eds.), *Perspectives and Trends in Education and Technology, Smart Innovation, Systems and Technologies*, Springer, Singapore, 253-267, doi:10.1007/978-981-16-5063-5_21

[2] Kliment, M.; Trebuna, P.; Pekarcikova, M.; Straka, M.; Trojan, J.; Duda, R. (2020). Production efficiency evaluation and products' quality improvement using simulation, *International Journal of Simulation Modelling*, Vol. 19, No. 3, 470-481, doi:10.2507/IJSIMM19-3-528

[3] Tamura, N. (2018). Optimal control of production with improvement, *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, Vol. 232, No. 6, 777-785, doi:10.1177/1748006X18761275

[4] Marschall, B.; Ochsenkuehn, D.; Voigt, T. (2022). Design and implementation of a smart, product-led production control using industrial agents, *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*, Vol. 3, No. 1, 48-56, doi:10.1109/JESTIE.2021.3117121

[5] Robertson, D.; Prucka, R. (2022). Evaluation of control-oriented flame propagation models for production control of a spark-assisted compression ignition engine, *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, Vol. 236, No. 2-3, 334-342, doi:10.1177/09544070211020842

[6] Zhang, T.-Q.; Malik, F. R.; Jung, S.; Kim, Y.-B. (2022). Hydrogen production and temperature control for DME autothermal reforming process, *Energy*, Vol. 239, Part A, Paper 121980, 11 pages, doi:10.1016/j.energy.2021.121980

[7] Parsanejad, M. (2019). An analysis of nonlinear inventory-production control system with production constraints, *International Journal of Industrial Engineering: Theory, Applications, and Practice*, Vol. 26, No. 4, 419-434, doi:10.23055/ijietap.2019.26.4.2429

[8] Tirkeş, G.; Çelebi, N.; Güray, C. (2021). Developing a multi-stage production planning and scheduling model for a small-size food and beverage company, *Journal Européen des Systèmes Automatisés*, Vol. 54, No. 2, 273-281, doi:10.18280/jesa.540209

[9] Angius, A.; Colledani, M.; Horvath, A. (2018). Lead-time-oriented production control policies in two-machine production lines, *IISE Transactions*, Vol. 50, No. 3, 178-190, doi:10.1080/24725854.2017.1417654

[10] Wang, J.; Yang, X.; Chen, C.-C.; Yang, S.-T. (2014). Engineering clostridia for butanol production from biorenewable resources: from cells to process integration, *Current Opinion in Chemical Engineering*, Vol. 6, 43-54, doi:10.1016/j.coche.2014.09.003

[11] Ojstersek, R.; Buchmeister, B. (2021). Simulation based resource capacity planning with constraints, *International Journal of Simulation Modelling*, Vol. 20, No. 4, 672-683, doi:10.2507/IJSIMM20-4-578

[12] Corton, J.; Donnison, I. S.; Patel, M.; Bühle, L.; Hodgson, E.; Wachendorf, M.; Bridgwater, A.; Allison, G.; Fraser, M. D. (2016). Expanding the biomass resource: sustainable oil production via fast pyrolysis of low input high diversity biomass and the potential integration of thermochemical and biological conversion routes, *Applied Energy*, Vol. 177, 852-862, doi:10.1016/j.apenergy.2016.05.088

[13] Liang, Q. (2020). Production logistics management of industrial enterprises based on wavelet neural network, *Journal Européen des Systèmes Automatisés*, Vol. 53, No. 4, 581-588, doi:10.18280/jesa.530418

[14] Maisonneuve, N.; Gross, G. (2011). A production simulation tool for systems with integrated wind energy resources, *IEEE Transactions on Power Systems*, Vol. 26, No. 4, 2285-2292, doi:10.1109/TPWRS.2011.2143437

[15] Deng, X.; Singh, R. B.; Liu, J.; Güneralp, B. (2016). Water productivity and integrated water resources management, *Physics and Chemistry of the Earth, Parts A/B/C*, Vol. 96, 1, doi:10.1016/j.pce.2016.11.002

[16] Wang, X.; Zhu, Y.; Sun, H.; Jia, F. (2018). Production decisions of new and remanufactured products: Implications for low carbon emission economy, *Journal of Cleaner Production*, Vol. 171, 1225-1243, doi:10.1016/j.jclepro.2017.10.053

[17] Machhammer, O.; Maaß, H.-J.; Bode, A. (2018). Production of electricity and liquid fuels with low carbon footprint, *Chemie Ingenieur Technik*, Vol. 90, No. 1-2, 212-225, doi:10.1002/cite.201700137

[18] Cao, K.; Xu, X.; Wu, Q.; Zhang, Q. (2017). Optimal production and carbon emission reduction level under cap-and-trade and low carbon subsidy policies, *Journal of Cleaner Production*, Vol. 167, 505-513, doi:10.1016/j.jclepro.2017.07.251

[19] Ahmed, M. A.; Arshad, A.; Anwar ul Haq, M.; Akram, B. (2020). Role of environmentalism in the development of green purchase intentions: a moderating role of green product knowledge, *International Journal of Sustainable Development and Planning*, Vol. 15, No. 7, 1101-1111, doi:10.18280/ijsdp.150714

[20] Chung, Y.; Paik, C.; Kim, H.; Kim, Y. J. (2017). Bottom-up analysis of GHG emissions from shipbuilding processes for low-carbon ship production in Korea, *Journal of Ship Production and Design*, Vol. 33, No. 3, 221-226, doi:10.5957/JSPD.33.3.160013

[21] Tokunaga, T.; Kishi, N.; Yamakawa, K.; Sasaki, K.; Yamamoto, T. (2017). Methane decomposition for hydrogen production by catalytic activity of carbon black under low flow rate conditions, *Journal of the Ceramic Society of Japan*, Vol. 125, No. 4, 185-189, doi:10.2109/jcersj2.16246

[22] Eisavi, B.; Ranjbar, F.; Nami, H.; Chitsaz, A. (2022). Low-carbon biomass-fueled integrated system for power, methane and methanol production, *Energy Conversion and Management*, Vol. 253, Paper 115163, 23 pages, doi:10.1016/j.enconman.2021.115163

[23] Kong, H.; Wang, J.; Zheng, H.; Wang, H.; Zhang, J.; Yu, Z.; Bo, Z. (2022). Techno-economic analysis of a solar thermochemical cycle-based direct coal liquefaction system for low-carbon oil production, *Energy*, Vol. 239, Part C, Paper 122167, 10 pages, doi:10.1016/j.energy.2021.122167

[24] Jiang, W.; Yu, X.; Yuan, H.; Zhang, M.; Shen, B.; Pan, Z.; Zhou, H. (2022). Alcoholysis approach for an efficient and cleaner production of diosgenin by low cost and green carbon based solid acids from biomass residues, *Journal of Cleaner Production*, Vol. 331, Paper 129974, 12 pages, doi:10.1016/j.jclepro.2021.129974

[25] Guizzi, G.; Falcone, D.; De Felice, F. (2019). An integrated and parametric simulation model to improve production and maintenance processes: towards a digital factory performance, *Computers & Industrial Engineering*, Vol. 137, Paper 106052, 14 pages, doi:10.1016/j.cie.2019.106052

[26] Nakamura, M.; Makihara, S.; Sugiura, J.-I.; Kamioka, Y. (2017). Dynamic optimization production system based on simulation integrated manufacturing and its application to mass production, *International Journal of Automation Technology*, Vol. 11, No. 1, 56-66, doi:10.20965/ijat.2017.p0056

[27] Dong, X.; Zhao, H.; Feng, Y.; Rong, G. (2015). Integrated optimization of CDU operation and production planning based on process simulation, *CIESC Journal*, Vol. 66, No. 1, 237-243

[28] Yu, J.; Ming, Z.; Wang, G.; Yan, Y.; Xi, H. (2018). Integrated simulation modeling method for complex products collaborative design using Engineering-APP, Luo, Y. (Ed.), *Cooperative Design, Visualization, and Engineering*, Springer, Cham, 200-208, doi:10.1007/978-3-030-00560-3_27