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Optimization configuration model for intelligent measurement multi-core modules considering "cloud-edge-end-core" collaboration

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ABSTRACT The new power system with new energy as the main body gives the low-voltage distribution network (LVDN) a richer connotation, requiring intelligent measurement equipment to have good scalability and collaborative ability. To address these requirements, an optimization configuration model for intelligent measurement multi-core modules considering "cloud-edge-end-core" collaboration is proposed in this paper. Initially, a technical framework for "cloud-edge-end-core" collaboration in intelligent measurement is designed, expanding the conventional "cloud-edge-end" vertical cooperation architecture with multi-core module collaboration and horizontal synergy at the same hierarchical level to enhance the flexibility of data interaction. Then, an optimization configuration model for multi-core modules is formulated, to minimize both the chip configuration costs and the data transmission costs associated with "cloud-edge-end-core" collaboration. The decision variables include the core chip level of the intelligent measurement terminal, the management core chip level for smart meters, and the placement of application configurations. Finally, the effectiveness of the proposed model is verified in the LVDN with 300 users. The performance of the proposed optimization configuration model in different scenarios is compared and the influence of model parameters on the optimization results is analyzed. The results show that the proposed multi-core module optimization configuration model can optimize the selection of intelligent measurement terminal core and smart meter management core according to different application data requirements. It meets the application requirements while minimizing the multi-core module optimization configuration cost and the "cloud-edge-end-core" collaboration cost.

INDEX TERMS Low-voltage distribution network; "cloud-edge-end-core" collaboration; intelligent measurement equipment; multi-core modules; optimization configuration model

Nomenclature

Abbreviations

LVDN	low-voltage distribution network

Indexes

i	index of intelligent measurement terminal core board level
j	index of smart meter management unit level

Variables

A_{E}	intelligent measurement terminal core board configuration cost, ¥
A_{D}	smart meter management unit configuration costs, ¥
A_{T}	data transmission cost between the edge and end side, ¥
A_{M}	equipment operation and maintenance cost, ¥
x_{Ei}	core board chip level configuration results of the i-th level intelligent measurement terminal, $x_{\mathrm{E}i} \in \{0, 1\}$

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x_{Dj}	chip level configuration results of the *j*-th level smart meter management unit
α	configuration position of the application
f	the objective of the multi-core module optimization configuration model for intelligent measuring equipment

Parameters

c_{Ei}	cost for the *i*-th level intelligent measurement terminal core board, ¥
I	total number of core board chip levels for intelligent measurement terminals that can be selected
Nu	number of smart meters in the coverage range of the intelligent measurement terminal
c_{Dj}	cost of the *j*-th level smart meter management unit, ¥
J	total number of chip levels of available smart meter management units
C_T	data transmission cost, ¥
d_1/ d_0	amount of data to be transmitted between the smart meter and intelligent measurement terminal when the application is configured on the smart metering terminal and smart metering terminal, respectively
m_E	maintenance cost of a single smart metering device, ¥
h_{Ei}	memory space of the *i*-th level chips on the intelligent measurement terminal core board, kb
h_{Di}	memory space of the *j*-th level chips on the smart meter management unit, kb
ϕ_T / ϕ_B	coefficients of storage space reserved for a single application by the intelligent measurement terminal core board and the smart meter management core, respectively
H_{s1}/ H_{s2}	data storage requirements of the function applied on the intelligent measurement terminal and smart meter, respectively, kb
D_s	data transmission requirement of the application
D_p	maximum transmission capacity of the communication channel between the smart measurement terminal and the smart meter

I. INTRODUCTION

The new power system with new energy as the main body gives the LVDN a richer connotation [1-2]. LVDN is developing in the direction of "new energy production and marketing integration", "distributed smart grid", and "supply and demand coordination and flexible interaction" [3-5]. This evolution puts forward higher requirements for intelligent measurement systems [6-7]. Operationally, it necessitates efficient synergy among cloud, edge, and end components of smart measurement, alongside optimized allocation of data and communication resources [8-9]. In terms of hardware, intelligent measurement equipment is required to have good scalability and coordination ability and can adapt to the growing demand for information collection, interaction, and complex algorithm execution [10].

Against this background, the multi-core module design of intelligent measurement equipment has attracted wide attention to enhance scalability and support "cloud-edge-end" collaboration [11-15]. Literature [13] designed the overall hardware circuit and software architecture of multi-core modular smart meters. In literature [14], a modular loosely coupled multi-core smart meter with four modules was designed, including a metering core, management core, identification core, and load control core. According to the new international standards, literature [15] designed multiple module cores, such as metering core, management core, communication core, and expansion module. It designed uplink communication, downlink communication, and expansion functions as pluggable and replaceable modular modes.

Deepened applications in LVDN, such as theft detection, power quality management, and topology recognition, are configured on smart measurement device modules [16-18]. The cost of "cloud-edge-end" collaborative data transmission for these applications is closely related to the location of application configuration and the capacity configuration of multi-core modules. Hence, for improving the collaborative efficiency of "cloud-edge-end" applications by LVDN, it is of great significance to research the optimization configuration of multi-core modules. However, the existing research [11-15] mainly focuses on the physical realization of hardware modular design. There is little research on optimizing multi-core module configurations which is the research object in this paper.

On the other hand, existing research on "cloud-edge-end" collaboration predominantly focuses on the optimized scheduling of resource tasks. There is little attention on the optimization of device configurations considering "cloud-edge-end" collaboration. In reference [19], a multidimensional collaborative resource scheduling method for the electric power internet of things is constructed based on a Federated Generative Adversarial Network. This method considers multidimensional collaboration and task offloading adversarial. Reference [20] considers pre-allocation and dynamic load balancing, aiming to maximize the average overall load balancing degree. It constructs an optimization configuration model for high-concurrency access of intelligent terminals under "cloud-edge-end" collaboration. For the cloud-based computation offloading for smart devices, Reference [21] proposes a fog-cloud architecture using queuing models and a stochastic gradient descent-based approach to optimize offloading probability and transmission power, thereby minimizing energy consumption, execution delay, and cost.

Table I summarize the approaches discussed in the above and the proposed approach. The cells marked with " √ " or "× " indicate whether specific issues and data are considered in each approach. In summary, further research is needed to optimize the configuration of multi-core modules with the objective of the total cost of "cloud-edge-end" collaboration minimization.

TABLE I. METHOD COMPARISON

Ref.	Object				
	Multi-core module design	"Cloud-edge-end" collaboration	"Cloud-edge-end-core" collaboration	Optimization of resource tasks	Optimization of multi-core module configuration
[11]	√	×	×	×	×
[12]	√	×	×	×	×
[13]	√	×	×	×	×
[14]	√	×	×	×	×
[15]	√	×	×	×	×
[19]	×	√	×	√	×
[20]	×	√	×	√	×
[21]	×	√	×	√	×
our work	√	√	√	×	√

The paper's motivation is to increase intelligent measurement equipment's scalability and collaborative ability by improving the existing "cloud-edge-end" collaboration architecture and optimizing the configuration of intelligent measurement multi-core modules. The main contributions are as follows.

1. A technical framework for "cloud-edge-end-core" collaboration in intelligent measurement is designed, augmenting the conventional "cloud-edge-end" vertical cooperation architecture with multi-core module collaboration and horizontal synergy at the same hierarchical levels to enhance the flexibility of data interaction in different levels.

2. The optimal configuration model of multi-core modules of intelligent measurement equipment is proposed, which can adapt to the application function requirements of the LVDN, optimize the core configuration of intelligent measurement equipment, and achieve the optimal comprehensive efficiency of "cloud-edge-end-core" collaboration of intelligent measurement.

The rest of this paper is organized as follows. Section II designs a "cloud-edge-end-core" collaboration framework. Then, Section III proposes the optimal configuration model for the intelligent measurement multi-core modules. Furthermore, in Section IV, the effectiveness of the proposed model is verified, and the comparison and sensitivity analysis are carried out. Lastly, Section V presents the conclusion of the study and future work.

II. "CLOUD-EDGE-END-CORE" COLLABORATION FRAMEWORK IN INTELLIGENT MEASUREMENT

The intelligent measurement system, also known as the advanced metering infrastructure, is composed of elements such as smart meters, concentrators, intelligent measurement terminals, cloud master stations, and communication networks [22]. Based on these elements, the "cloud-edge-end" collaboration integrates technologies such as cloud computing, big data, and edge computing to optimize the allocation of operation, data, and communication resources. With the cloud side serving as the computational platform, and the edge and end sides acting as the sensory inputs, it achieves cloud-based decision-making and collaborative control for the power grid. This provides "cloud-edge-end" bidirectional data, operation, and application service collaboration for optimal operation and management of the distribution network, and its architecture is a single vertical structure [23].

As shown in Figure 1, this section extends the existing intelligent measurement "cloud-edge-end" collaboration framework horizontally and vertically to form a "cloud-edge-end-core" collaboration technical framework including vertical enhancement and horizontal expansion. In the vertical, the incorporation of multicore module collaboration is added. This refinement allows the granularity of collaboration to be further dissected and extended down to the level of individual modules within smart measurement terminals and smart meters. In the horizontal, the interaction between devices at the same level is added and enables horizontal interaction between devices at the same layer, such as cloud-to-cloud, edge-to-edge, and end-to-end communication.

On the cloud side, the measurement master station, vertically, facilitates the realization of various extended functions in LVDN by information dissemination and data receipt from the smart measurement terminals. Horizontally, it engages in information exchange with other master stations such as the marketing master and dispatch master, receiving data requests and forwarding relevant data. Serving as the computational nerve center of the entire system, the cloud major station enables big data analysis and neural network training capabilities. As the computing power center of the whole system, the cloud master station realizes functions such as big data analysis and neural network training to realize cloud decision-making and collaborative control of the power grid with the cloud as the computing platform and the edge and end as the edge neural input.

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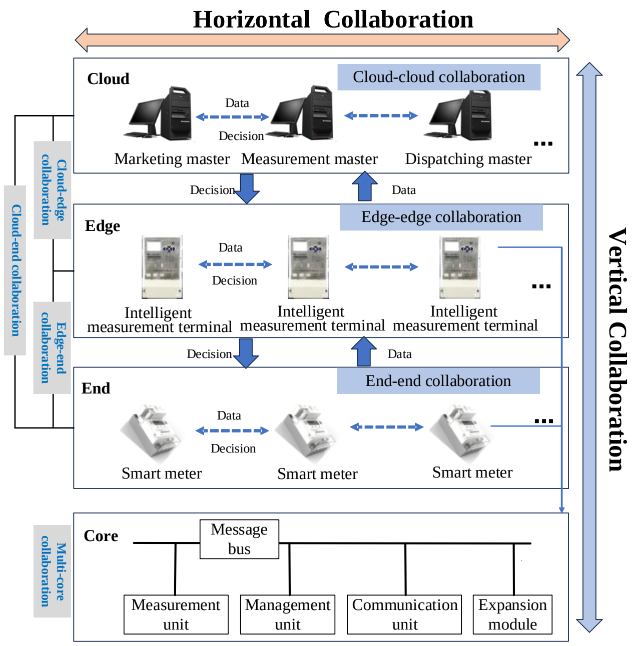

FIGURE 1. **Intelligent measurement "cloud - edge - end - core" collaborative framework**

On the edge side, the intelligent measurement terminal sends data requests and receives data to the smart meter vertically, and can also analyze the station data based on limited computing power, such as station topology identification, line loss anomaly monitoring, household variation relationship identification, etc. It can exchange information with intelligent measuring terminals of other stations in the horizontal direction, send and receive the data analysis results of this station to other intelligent measuring terminals, and carry out cross-verification further.

On the end side, smart meters measure and collect the user's electricity consumption data. Vertically, the smart meter interacts with the intelligent measuring terminal, receives data requests, and uploads data. It can also realize a load identification function based on the user's power consumption data. Horizontally, smart meters communicate with other smart meters for data interaction.

Core refers to the multi-core modules inside the smart measurement terminal and the smart electricity meter. In the multi-core modules collaboration, these modules are interconnected through a message bus. Utilizing a unified structured data model, the traditional one-to-one communication pattern between modules is changed. This approach enables communication between any modules, thus broadening the range of module interaction. This enhancement in modularity interaction is conducive to improving the operational efficiency of the combined multicore modules within intelligent measurement terminals and smart meters.

By extending both horizontally and vertically, the proposed "cloud-edge-end-core" collaborative framework evolves into a mesh-like network, decentralizing the previously centralized vertical information interaction pattern. This transformation empowers the smart measurement system with the ability for peer-to-peer communication at the same level, which can significantly enhance the flexibility of information interaction within the intelligent measurement system.

The identification of the transformer-user relationship in LVDN is taken as an example to elaborate the advantages of the "cloud-edge-end-core" collaborative framework with a mesh-like network structure. In the signal injection method for identifying the transformer-user relationship, the intelligent measurement terminal sends a modulated current signal to the smart meter. Smart meters belonging to the specific LVDN then provide feedback to the terminal upon receiving the signal. Conversely, those smart meters that do not respond to the signal are indicative of erroneous transformer-to-customer relationships.

The information transmission process of identification of the transformer-user relationship under the two cooperative frameworks is shown in Figure 2. Under the single vertical structure of the "cloud-edge-end" cooperation framework, intelligent measurement terminals on the edge side cannot communicate with each other, so the signal injection method can only identify the users who have the wrong transformer-user relationship but cannot confirm their real affiliations. Under the "cloud-edge-end-core" mesh network structure, edge-edge collaboration permits communication between adjacent intelligent measurement terminals, allowing them to share information about users with incorrect transformer-user relationships. By cross-comparing these users' internal receiving modulation current information with the modulation current information delivered by the terminal of the station, the accurate household relation of these users can be determined, and the identification accuracy of the station's household relation can be greatly improved.

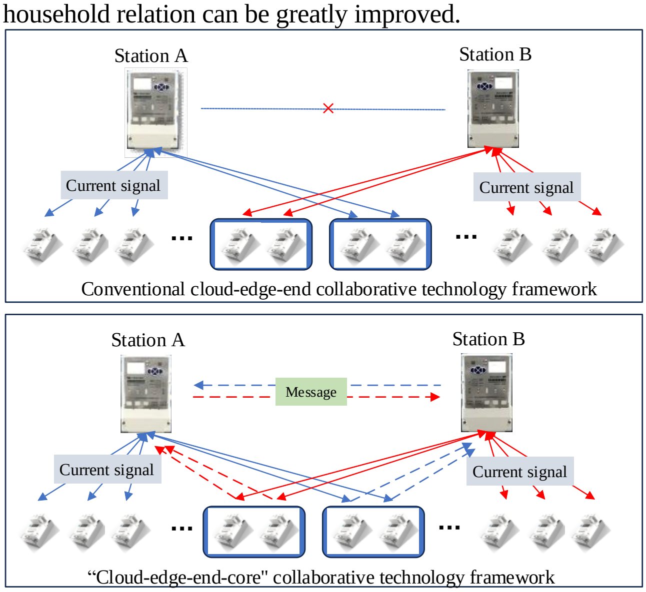

FIGURE 2. **The information transmission process of identification of the transformer-user relationship under the two cooperative frameworks**

III. MULTI-CORE MODULE OPTIMAL CONFIGURATION MODEL

The intelligent measurement "cloud-edge-end-core" collaboration framework designed in Section 1 provides an information interaction path of data and decision-making for LVDN deepening applications. This section focuses on the multi-core module of intelligent measuring equipment, which carries LVDN's deepening application. Based on Section 1, the cost of the "cloud-edge-end-core" collaborative process is considered, and the multi-core module optimization configuration model is proposed.

In the process of cloud-end-edge-core collaboration, the difference in resources and costs required for allocating the same application to different levels is significant. The proposed optimal model aims to minimize the "cloud-edge-end-core" collaborative comprehensive cost, which includes the core board of the intelligent measuring terminal, the configuration cost of the smart meter management unit, the data transmission cost, and equipment operation and maintenance cost. The model takes the chip level of the core board of the intelligent measuring terminal, the chip level of the smart meter management unit, and the application configuration position as the decision variables, as shown in Figure 3. It is worth noting that the multi-core module is the hardware module of intelligent measurement equipment on the edge and end side, so only the deepening applications configured on the edge and end are considered.

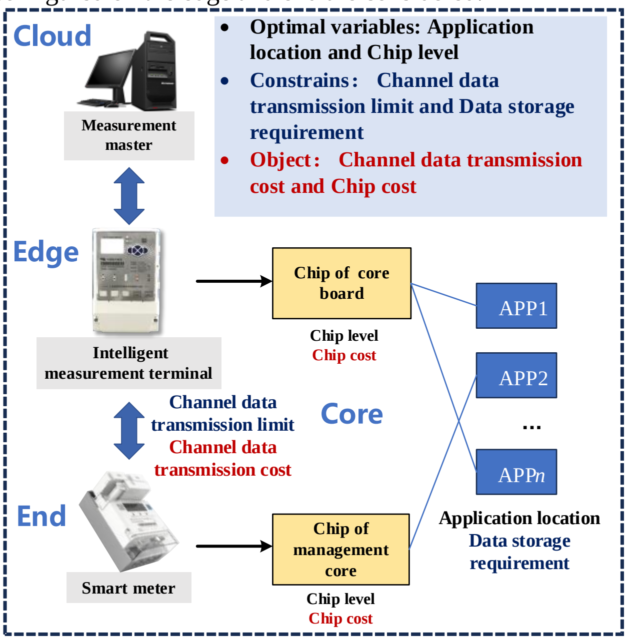

FIGURE 3. **Schematic diagram of multi-core module configuration model considering "cloud-edge-end-core" collaborative**

A. MODEL OPTIMIZATION OBJECTIVE

The collaborative process requires module chip calculation and data storage, data transmission in the communication channel, and equipment operation and maintenance. Therefore, the comprehensive cost considers the configuration cost of the intelligent measurement terminal core board, the configuration cost of the intelligent meter management unit, the data transmission cost, and the equipment operation and maintenance cost. The specific details are as follows.

1. Intelligent measurement terminal core board configuration cost A_{E} on the edge side

The chip level on the intelligent measurement terminal core board is determined by its storage space. The larger the storage space, the higher the chip level, and the higher its price. The configuration cost A_{E} is determined by multiplying the one-dimensional price row matrix with the one-dimensional chip configuration column matrix, as shown below:

$$A_{\mathrm{E}} = \sum_{i=1}^{I} c_{\mathrm{E}i} \cdot x_{\mathrm{E}i} \tag{1}$$

Where $c_{\mathrm{E}i}$ is the cost for the i-th level intelligent measurement terminal core board; $x_{\mathrm{E}i}$ is the core board chip level configuration results of the i-th level intelligent measurement terminal, $x_{\mathrm{E}i} \in \{0, 1\}$, i=1, …, I; I is the total number of core board chip levels for intelligent measurement terminals that can be selected.

2. Smart meter management unit configuration costs A_{D} on the end side

The number of smart meters in the coverage range of the intelligent measurement terminal is Nu. The configuration cost of the smart meter management unit in LVDN is the sum of the configuration costs of Nu smart meters in the LVDN. Like the core board of the smart measurement terminal, the chip level of a single smart meter management unit is determined by its storage space. The larger the storage space, the higher the chip level, and the higher the price. The A_{D} is shown below:

$$A_{\mathrm{D}} = \mathrm{N_u} \sum_{j=1}^{J} c_{\mathrm{D}j} \cdot x_{\mathrm{D}j} \tag{2}$$

Where $c_{\mathrm{D}j}$ is the cost of the j-th level smart meter management unit; $x_{\mathrm{D}j}$ is the chip level configuration results of the j-th level smart meter management unit, $x_{\mathrm{D}j} \in \{0, 1\}$, j=1, …, J; J is the total number of chip levels of available smart meter management units.

3. Data transmission cost A_{T} between the edge and end side

The communication channel between the intelligent measurement terminal and the smart meters restricts the amount of data transmission between the edge side and the end side. At the same time, the more the number of data transmission, the lower the reliability of data transmission. The location of the application configuration affects the amount of data transferred between edges, and the A_{T} is as follows:

$$A_{\mathrm{T}} = \mathrm{C_T} \mathrm{N_u} [\alpha \mathrm{d}_1 + (1-\alpha)\mathrm{d}_0] \tag{3}$$

Where α indicates the configuration position of the application; α=1 indicates that the application is configured on the intelligent measurement terminal; α=0 indicates that the application is configured on the smart meter; $\mathrm{C_T}$ is the data transmission cost; d_1 and d_0 are the amount of data to be transmitted between the smart meter and intelligent measurement terminal when the application is configured on

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the smart metering terminal and smart metering terminal, respectively.

4. Equipment operation and maintenance cost A_M

After the module is put into use, regular operation and maintenance are required to ensure the reliability of the module. Equipment operation and maintenance require manual service, and the workload of manual service is related to the total number of meters in the LVDN, as shown below:

$$A_M = m_E \cdot (N_u + 1) \tag{4}$$

Where m_E is the maintenance cost of a single smart metering device.

In summary, the objectives of the multi-core module optimization configuration model for intelligent measuring equipment are as follows:

$$\begin{aligned} f &= \min(A_E + A_D + A_T + A_M) \\ &= \sum_{i=1}^{I} c_{Ei} \cdot x_{Ei} + N_u \sum_{j=1}^{J} c_{Dj} \cdot x_{Dj} + C_T N_u[\alpha d_1 + (1-\alpha)d_0] \\ &+ m_E \cdot (N_u + 1) \end{aligned} \tag{5}$$

B. MODEL CONSTRAINTS

The model constraints of optimal configuration of the intelligent measurement system in LVDN include application function data storage constraints, transmission constraints, and decision variable constraints, which are as follows.

1. Application function data storage constraints

Data storage for input data and calculation processes is required when application functions are carried out. Hence, the chip of the intelligent measurement terminal core board and smart meter management unit must be able to meet the data storage requirements of application functions. Since the application functions are configured in different locations, the required storage space varies. The design of the application configuration variable α is subject to the following constraints:

$$\alpha(\varphi_T \sum_{i=1}^{I} h_{Ei} x_{Ei}) + (1-\alpha)(\varphi_B \sum_{j=1}^{J} h_{Dj} x_{Dj}) \geq \alpha H_{s1} + (1-\alpha) H_{s2} \tag{6}$$

Where α indicates the configuration position of the application; h_{Ei} is the memory space of the i-th level chips on the intelligent measurement terminal core board; h_{Di} is memory space of the j-th level chips on the smart meter management unit; ϕ_T and ϕ_B are the coefficients of storage space reserved for a single application by the intelligent measurement terminal core board and the smart meter management core, respectively; H_{s1} and H_{s2} are the data storage requirements of the function which applied on the intelligent measurement terminal and smart meter, respectively.

2. Data transmission constraints

Data required in the application function is transmitted by the communication module between the intelligent measurement terminal and the smart meter. Since the application functions are configured in different locations, the amount of data that needs to be transmitted varies. The data transmitted between the smart measurement terminal and the smart meter must be no less than the data required for the application functions, and at the same time, it cannot exceed the transmission capacity of the communication channel between the smart measurement terminal and the smart meter. Specifically, it is as follows:

$$D_s \leq \alpha d_1 N_u + (1-\alpha) d_0 N_u \leq D_p \tag{7}$$

Where D_s is the data transmission requirement of the application; D_p is the maximum transmission capacity of the communication channel between the smart measurement terminal and the smart meter.

3. Decision variable constraints

The decision variables in the proposed optimal configuration model include the core board chip level configuration variable of intelligent measurement terminal x_{Ei}, the chip level configuration variable of smart meter management unit x_{Dj}, and the configuration position of the application α. During the optimization configuration process, there is only one option for the selection of the smart measurement terminal core board chip level, the smart meter management unit chip level, and the application configuration location. α is a 0-1 Boolean variable that meets the requirements. To ensure the uniqueness of the configuration results, the following constraints are imposed on x_{Ei} and x_{Dj}.

$$\sum_{i=1}^{I} x_{Ei} = 1, x_{Ei} \in \{0,1\} \tag{8}$$

$$\sum_{i=1}^{J} x_{Dj} = 1, x_{Dj} \in \{0,1\} \tag{9}$$

In summary, the optimal configuration model of multi-core modules of intelligent measuring equipment is given by Equation (10).

$$\begin{aligned} & f = \min \sum_{i=1}^{I} c_{Ei} \cdot x_{Ei} + N_u \sum_{j=1}^{J} c_{Dj} \cdot x_{Dj} + C_T N_u[\alpha d_1 + (1-\alpha)d_0] \\ & + m_E \cdot (N_u + 1) \\ & s.t. \\ & \alpha(\varphi_T \sum_{i=1}^{I} h_{Ei} x_{Ei}) + (1-\alpha)(\varphi_B \sum_{j=1}^{J} h_{Dj} x_{Dj}) \geq \alpha H_{s1} + (1-\alpha) H_{s2} \\ & D_s \leq \alpha d_1 N_u + (1-\alpha) d_0 N_u \leq D_p, \alpha \in \{0,1\} \\ & \sum_{i=1}^{I} x_{Ei} = 1, x_{Ei} \in \{0,1\} \\ & \sum_{i=1}^{J} x_{Dj} = 1, x_{Dj} \in \{0,1\} \end{aligned} \tag{10}$$

Where α indicates the configuration position of the application; h_{Ei} is the memory space of the i-th level chips on the intelligent measurement terminal core board; h_{Di} is the memory space of the j-th level chips on the smart meter management unit; ϕ_T and ϕ_B are the coefficients of storage space reserved for a single application by the intelligent measurement terminal core board and the smart meter management core, respectively; H_{s1} and H_{s2} are the data storage requirements of the function which applied on the intelligent measurement terminal and smart meter, respectively; D_s is the data transmission requirement of the application; D_p is the maximum

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transmission capacity of the communication channel between the smart measurement terminal and the smart meter.

Equation (10) is an integer nonlinear programming problem, which falls into the category of NP problems. The presence of integer variables significantly increases the difficulty of finding a solution. To enhance the solving speed and improve solvability, the integer variables in Equation (10) are relaxed to continuous variables. Specifically, the conditions α, x_{Ei}, x_{Dj} $\in\{0,1\}$ are changed to α, x_{Ei}, x_{Dj} $\in[0,1]$. Additionally, constraints that encourage these variables to take values close to either 0 or 1 are introduced, as shown in Equation (11). With this relaxation, Equation (10) is transformed from an integer nonlinear programming problem into a nonlinear programming problem, thereby reducing the complexity of the solution process.

$$\begin{aligned}
& f=\min\sum_{i=1}^{I}c_{\mathrm{E}i}\cdot x_{\mathrm{E}i}+\mathrm{N_u}\sum_{j=1}^{J}c_{\mathrm{D}j}\cdot x_{\mathrm{D}j}+\mathrm{C_T}\mathrm{N_u}[\alpha\mathrm{d}_1+(1-\alpha)\mathrm{d}_0] \\
& +m_{\mathrm{E}}\cdot(\mathrm{N_u}+1) \\
& s.t. \\
& \alpha(\varphi_{\mathrm{T}}\sum_{i=1}^{\mathrm{I}}h_{\mathrm{E}i}x_{\mathrm{E}i})+(1-\alpha)(\varphi_{\mathrm{B}}\sum_{j=1}^{\mathrm{J}}h_{\mathrm{D}j}x_{\mathrm{D}j})\geq\alpha\mathrm{H_{s1}}+(1-\alpha)\mathrm{H_{s2}} \qquad (11)\\
& \mathrm{D_s}\leq\alpha\mathrm{d_1}\mathrm{N_u}+(1-\alpha)\mathrm{d_0}\mathrm{N_u}\leq\mathrm{D_p},\alpha\in[0,1] \\
& \sum_{i=1}^{I}x_{\mathrm{E}i}=1, x_{\mathrm{E}i}\in[0,1] \\
& \sum_{i=1}^{J}x_{\mathrm{D}j}=1, x_{\mathrm{D}j}\in[0,1] \\
& x_{\mathrm{E}i}(1-x_{\mathrm{E}i})=0 \\
& x_{\mathrm{D}i}(1-x_{\mathrm{D}i})=0 \\
& \alpha(1-\alpha)=0
\end{aligned}$$

YALMIP is a free MATLAB toolbox that provides a high-level modeling language for formulating various optimization problems, including linear, nonlinear, quadratic, and semidefinite programming. It interfaces with multiple solvers, making it a versatile tool for solving complex optimization tasks. Hence, the proposed optimization model can be solved by the solver of IPOPT in the YALMIP.

IV. CAST STUDY

In this section, an LVDN with 300 users is taken as an example to conduct the optimal configuration of multi-core modularization of intelligent measurement devices. The case studies for verification include four sections: 1) the description of the case parameters; 2) the model optimization procedure, detailing how the proposed model can optimize the configuration of multi-core modules of intelligent measurement equipment; 3) the comparative analysis showcasing the model's performance across divergent scenarios; 4) investigation into the influence of parameter settings within the model on the outcomes of multicore module optimization configurations.

A. CASE PARAMETERS

c_{Ei}, c_{Dj}, I, J, h_{Ei}, C_T, and h_{Di} are determined based on market product capacity information and pricing. Nu is determined by the user number in the LVDN. d_1/ d_0, H_{s1}/H_{s2}, D_s, and D_p are determined by the data requirement of the application. m_E, ϕ_T / ϕ_B is determined by engineering experience. The storage capacity and prices of different levels of chips for the core board of the intelligent measurement terminal and the management unit of smart meters are shown in Table II.

Smart meters' voltage, current, and active power single point data occupy 6, 9, and 12 bytes respectively, with one measurement point. In terms of data transmission, the intelligent measuring terminal can only receive a maximum of 60 messages per minute, which amounts to 86,400 messages per day. Considering the communication channel requirements of other functions in the low-voltage power distribution area, the maximum communication capacity between the intelligent measuring terminal and the smart meters for a single application is set to 60% of the total, with Dp=51,840 messages per day. The cost of the communication module of the intelligent measuring terminal is 250 ¥ per piece, and the cost of the communication module of the smart meter is 50 ¥ per piece. The example LVDN includes one communication module of the intelligent measuring terminal and 300 communication modules of smart meters, with a total cost of 15,250 ¥. A single message communication on the end-to-edge side costs C_T approximately 0.18 ¥ per message. The maintenance cost of a single intelligent measuring equipment is set at 10 ¥. Based on engineering experience, the coefficients of storage space reserved for a single application by the intelligent measurement terminal core board ϕ_T is set to 10%, and the coefficients of storage space reserved for a single application by the smart meter management core ϕ_B is set to 20%.

TABLE II. THE STORAGE CAPACITY AND PRICES OF DIFFERENT LEVELS OF CHIPS FOR THE CORE BOARD OF THE INTELLIGENT MEASUREMENT TERMINAL AND THE MANAGEMENT UNIT OF SMART METERS

The core board of the intelligent measurement terminal			**The management unit of smart meters**		
Level	storage capacity	Price (¥)	Level	storage capacity	Price (¥)
T1	1G	10	M1	8Mb	2.8
T2	4G	25	M2	16Mb	5
T3	8G	45	M3	32Mb	11
T4	16G	75			

B. MEDEL OPTIMIZATION PROCEDURE

In this section, the application scenario of low-voltage topology recognition is taken as an example to demonstrate the implementation process of the proposed optimization configuration model.

1. Ensure the data storage requirements for the low-voltage topology identification

The application requires voltage, current, and active power values from all smart meters within the coverage area of the edge-side smart measurement terminal, with measurements taken once per minute, for a total duration of 15 days. The total

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storage space required for those data of a single smart meter over 15 days is (6+9+12)* 60*24*15≈570 kb. For an LVDN with 300 users, a total of about 167Mb of storage space is required.

2. Ensure the amount of data transmitted between the intelligent terminals and smart meters

When the low-voltage topology identification function is configured on the intelligent measuring terminal, it needs to collect voltage, current, and active power data from all smart meters in the LVDN. These data are transmitted to the intelligent measuring terminal every 15 minutes. Each smart meter needs to transmit d_1=4*24 = 96 messages to the intelligent measuring terminal. In this case, the amount of data transmission required for the low-voltage topology identification application is 4*24*300 = 28,800 messages.

When the low-voltage topology identification function is configured on the smart meter, the intelligent measuring terminal only collects the topology results of the smart meters. The value of the message d_0 that needs to be transmitted from a single smart meter to the intelligent measuring terminal is 1. In this case, the minimum amount of data transmission required for the low-voltage topology identification application is 1*300=300 messages.

In summary, the end-to-edge data transmission demand Ds for the low-voltage topology identification function takes the minimum value under the above two configurations, which is 300 messages.

3. Multi-core module optimization configuration model

The above parameters are brought into the optimization configuration model in equation (11) to solve the configuration results, as shown in Figure 3. Based on the parameters of the intelligent measurement terminal core and the intelligent meter management core in Table I, the multi-core module of the intelligent measurement equipment in the example LVDN is optimized as follows: The core board of the intelligent measurement terminal is selected T2 with 4GB memory; Smart meter management unit selected M1, with 8MB memory, application configuration in the side of the smart measurement terminal.

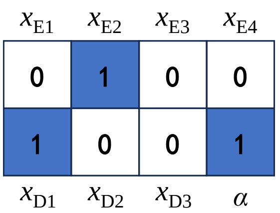

FIGURE 4. Multi-core module optimization configuration results for low voltage topology recognition

Currently, the total configuration costs of the core board of the intelligent measuring terminal and the smart meter management unit are 9059 ¥. The total configuration cost of the intelligent measurement terminal core board and smart meter management core is 865 ¥ and the data communication cost is 5,184 ¥. The total maintenance cost is 3010 ¥. The low-voltage topology identification function is applied to the intelligent measuring terminal mainly because the amount of data required for low-voltage topology identification is 570kb, which is difficult for the smart meter management unit's storage space to satisfy. However, the 4G memory of the core board of the intelligent measuring terminal can meet its storage demand of 167Mb when applied to the terminal. It is worth mentioning that the application of low-voltage topology identification on the intelligent measuring terminal significantly increases the data communication cost, as smart meters transmit data to the intelligent measuring terminal daily.

Further, the optimization is performed in 5 low-voltage stations with different topologies and users, and the influence of changes in the number of users on the optimization results is compared and analyzed, as shown in Table III. It can be seen from Table II that when the user number increases, the module capacity of the core board of the intelligent measurement terminal increases, as well as the total configuration cost. However, the variable number has no change. Hence, the change in user number does not increase the complexity and operation effort of the model.

TABLE III. OPTIMIZATION RESULTS UNDER 5 LVDNS

	User number	Total cost (¥)	The core board of the intelligent measurement terminal	The management unit of smart meters	Application configuration location	Variables number
LVDN1	126	3800.08	T1(1GB)	M1(8MB)	1	8
LVDN2	272	8206.76	T2(4GB)	M1(8MB)	1	8
LVDN3	300	9049	T2(4GB)	M1(8MB)	1	8
LVDN4	434	13079.72	T2(4GB)	M1(8MB)	1	8
LVDN5	470	14162.6	T2(4GB)	M1(8MB)	1	8

C. COMPARATIVE ANALYSIS

The existing research mainly focuses on the physical realization of hardware modular design, i.e. ref.[11]~ref.[15] and the optimized scheduling of resource tasks i.e. ref.[19]~ref.[21]. However, this paper focuses on the optimization of multi-module configurations considering "cloud-edge-end" collaboration. Hence, It's hard to compare the research works in ref.[11]~ref.[15], ref.[19]~ref.[21] and the proposed method in the case study. Instead, this section mainly compares the proposed method with the traditional method in which multi-core module configuration selects the middle value. Four scenarios are established as follows.

Scenario 1: Multi-module configuration for low-voltage topology identification applications with the proposed optimal configuration model;

Scenario 2: Multi-module configuration for low-voltage topology identification applications with the traditional method;

Scenario 3: Multi-module configuration for power quality monitoring applications with the proposed optimal configuration model;

Scenario 4: Multi-module configuration for power quality monitoring applications with the traditional method.

The optimal configuration results of multi-core modules in different application scenarios are compared between Scenario 1 and Scenario 3. The impact of using or not using the optimization configuration model under two application scenarios is compared between Scenario 1 and Scenario 2, and Scenario 3 and Scenario 4, respectively. The configuration results of the four scenarios are shown in Table IV, and the cost is shown in Figure 5. It is worth noting that the equipment operation and maintenance cost is related to the number of intelligent measuring devices in LVDN, and the number of devices in the four scenarios is unchanged, so the equipment operation and maintenance costs are not compared in Figure 5.

TABLE IV. THE STORAGE CAPACITY AND PRICES OF DIFFERENT LEVELS OF CHIPS FOR THE CORE BOARD OF THE INTELLIGENT MEASUREMENT TERMINAL AND THE MANAGEMENT UNIT OF SMART METERS

Scenarios	The core board of the intelligent measurement terminal	The management unit of smart meters	Application location
Scenario 1	T2（4GB）	M1(8MB)	1
Scenario 2	T3（8GB）	M2(16MB)	1
Scenario 3	T1（1GB）	M1(8MB)	0
Scenario 4	T1(1GB)	M1(8MB)	1

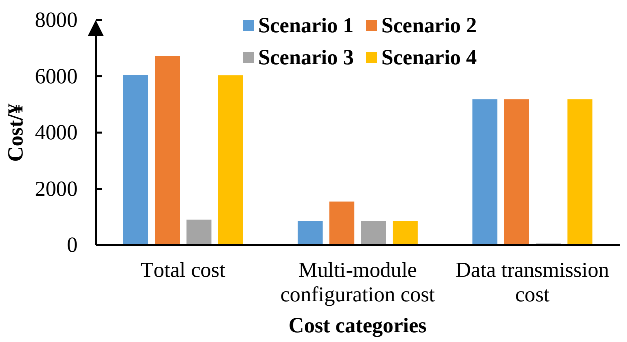

FIGURE 5. **Cost for four scenarios**

Combined with Table IV and Figure 5, the analysis is as follows:

1. Comparative Analysis between Scenario 1 and Scenario 2: The low-voltage topology identification application requires large data, and the end-side smart meter management core memory is insufficient. Therefore, both scenarios' applications are configured on the edge-side intelligent measurement terminal, and the data transmission cost is the same. Scenario 2 with the traditional method whose multi-core module configuration selects the middle value, then the multi-core module configuration cost increases by 680 ¥ compared with Scenario 1.

2. Comparative Analysis between Scenario 3 and Scenario 4: The multi-core module selection in Scenario 3 and Scenario 4 is the same. However, in Scenario 3, the power quality monitoring application is configured on the end-side smart meter through the optimization configuration model. In contrast, in Scenario 4, the application is configured on the edge-side intelligent measurement terminal with the traditional method. In this case, compared with Scenario 3, Scenario 4 significantly increases the cost of data transmission between edges, and the total cost of Scenario 4 is 6 times greater than that of Scenario 3.

3. Comparative Analysis between Scenario 1 and Scenario 3: Due to the different data requirements of Scenario 1 and Scenario 3, the optimal configuration model configs the two applications in the edge-side intelligent measurement terminal and the end-side smart meter respectively. In Scenario 1, the amount of data transmitted through the communication channel increases. Therefore, the chip memory selected by the intelligent measurement terminal in scenario 1 is larger than in scenario 3. At the same time, the data transfer and total cost of Scenario 1 are much higher than that of Scenario 3.

In summary, compared with the average selection of configuration, the proposed optimal configuration model can save the cost of "cloud-edge-end" data transmission and multi-core module configuration. The optimal configuration model can adapt to the data requirements of different applications and give the configuration results.

D. SENSITIVITY ANALYSIS FOR PARAMETERS IN THE MODEL

The proposed multi-core module optimization configuration model includes two parameters, namely, the storage space coefficient ϕ_T and ϕ_B reserved for a single application by the intelligent measurement terminal core board and the intelligent meter management core. This section uses the application of low-voltage topology identification as an example to analyze the impact of the two parameters on the optimal configuration of multi-core modules.

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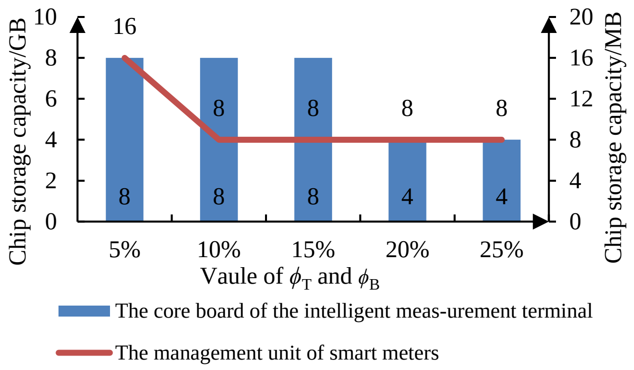

FIGURE 6. Parameter influence analysis result

As shown in Figure 6, the values of ϕ_T and ϕ_B directly affect the configuration results of multi-core modules. When ϕ_T is less than 15%, the core configuration capacity of the intelligent measurement terminal is 8GB, and when ϕ_T is greater than 15%, the core configuration capacity of the intelligent measurement terminal can be reduced to 4GB, and the larger value of ϕ_T is conducive to reducing the configuration cost of the intelligent measuring terminal core. Similarly, when ϕ_B is less than 5%, the configuration capacity of the smart meter management core needs to be 16MB, when ϕ_B is greater than 5%, the configuration capacity of the smart meter management core can be reduced to 8MB, and the larger value of ϕ_B is conducive to reducing the configuration cost of the smart meter management core.

V. CONCLUSION

In this paper, an intelligent measurement multi-core module optimization configuration model considering "cloud-edge-end-core" collaboration is proposed. The conclusions are as follows:

1) The intelligent measurement "cloud-edge-end-core" collaborative technology architecture was designed. The horizontal and vertical collaboration decentralized the existing vertical centralized collaborative architecture, and the intelligent measurement system has the ability of peer neighborhood communication, which can improve the flexibility of information interaction of the intelligent measurement equipment. The granularity refinement of collaboration is extended to the collaboration of various modules inside intelligent measurement terminals and smart meters, and the combined operation efficiency of multi-core modules inside intelligent measurement equipment is improved.

2) A multi-core module optimization configuration model considering "cloud-edge-end-core" collaboration is proposed. The case study shows that the proposed model can optimize the chip level and application configuration position of the core board of the intelligent measurement terminal and smart meter management unit according to the data requirements of different application functions in the low voltage station area, and reduce the chip configuration cost and data transmission cost.

3) Compared with the average selection of configuration, the proposed optimal configuration model can save the cost of "cloud-edge-end" data transmission and multi-core module configuration. The values of ϕ_T and ϕ_B directly affect the configuration results of multi-core modules, the larger values of ϕ_T and ϕ_B are conducive to reducing the configuration cost of the intelligent measuring terminal core and of the smart meter management core.

There are several assumptions and limitations in the proposed approach: 1) the proposed "cloud-edge-end-core" collaboration framework assumes that communication and information transfer between different modules are secure and reliable; 2) the task resource scheduling optimization is not considered; 3) the multi-core module optimization configuration model only considers the data storage and transmission requirements of a single application through the threshold coefficient. In the future, the optimization of multi-core module configurations under the simultaneous resource optimization and scheduling of multiple applications will be studied, considering the impact of security and reliable factors on data transmission.

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