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Intelligent Fluid-Driven Active Thermal Management Systems: Multi-physics Modeling and Predictive Control Optimization

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Abstract. To address the bottleneck in thermal management of high power density electronic devices, an active thermal management system architecture based on intelligent fluid drive is proposed in this paper. In this study, a dynamic model covering electric-flow-thermal multi-physical field coupling is constructed, and the intrinsic orthogonal decomposition technology is used to break through the computational power barrier of high-dimensional nonlinear systems, which provides an important theoretical paradigm and engineering path for the next generation of adaptive intelligent thermal control technology.

Keywords: Intelligent fluid, Active thermal management, Model order reduction, Multi-physics Field modeling

1. Introduction

With the integration level of microelectronic devices approaching the atomic level, the traditional mechanical pump-driven cooling paradigm is limited by physical limits, which has been difficult to deal with the "thermal barrier" crisis caused by transient high thermal shock [1]. In this context, the intelligent fluid working medium based on electro-magnetic fluid dynamics provides a disruptive technical path for the construction of adaptive active thermal management system by virtue of its mechanical component-free, field-driven and rheological controllable characteristics, and becomes a key frontier to break through the existing thermal control barriers [2,3].

As shown in Figure 1, although smart fluids have accumulated considerable theoretical foundation in enhancing heat transfer mechanism, there are still significant technical shortcomings in the existing research system at the system-level application level. First, the existing literature focuses on the characterization of steady-state heat transfer characteristics under a single physical field, and lacks the systematic description of the evolution law of rheological constitutive and convective heat transfer coefficient of dynamic working medium under the action of unsteady external field, resulting in serious distortion of the prediction accuracy of the model under dynamic load [4,5]. Second, the current control means of intelligent fluid thermal management system still mainly stay at the level of open-loop regulation or classical PID feedback control, which cannot

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realize the global optimal planning of driving energy consumption under the premise of meeting the temperature control constraints [6,7].

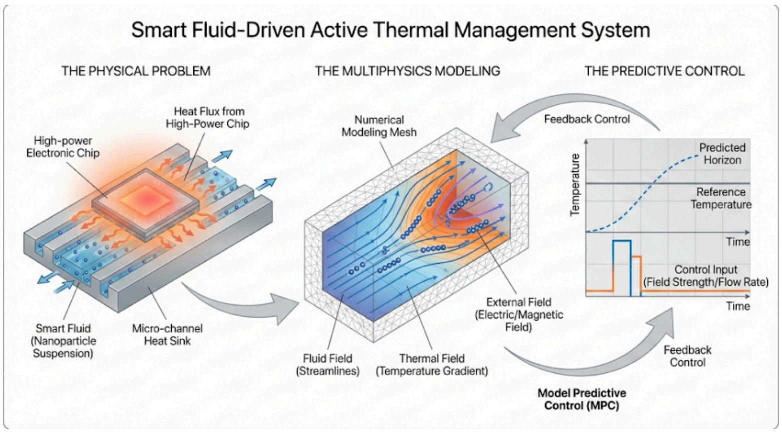

Figure 1. Schematic diagram of the study logic

In view of this, this paper aims to construct a multi-physical field state space model that integrates fluid dynamics, thermodynamics and electromagnetism, and reveals the active response mechanism of intelligent fluid under dynamic field. On this basis, the model predictive control algorithm is introduced. This is not only a deepening of the multi-physical field coupling theory, but also a key exploration of the engineering implementation of intelligent thermal control technology.

2. Multiphysics modeling

In this study, based on the continuum mechanics framework, a multi-physics coupling equation set covering electric field, flow field and temperature field is established for the flow heat transfer behavior of intelligent fluid in a microchannel. Firstly, Maxwell stress tensor is introduced to characterize the volume force generated inside the fluid under the external field [8], and its shear viscosity η explicitly depends on the local field strength E and temperature T.

The finite volume method is further used to discretize the computational domain in space, and the infinite dimensional distributed parameter system is transformed into a finite dimensional ordinary differential equation system [9]. Using the Galerkin projection method [10], the prime dynamical equations are projected into the low-dimensional subspace spanned by these eigenmodes, and a reduced-order state space model of the following form is constructed:

$$\dot{x}(t) = Ax(t) + Bu(t) + Dd(t) \tag{1}$$

$$y(t) = Cx(t) \tag{2}$$

Here, x(t) is the state vector after dimension reduction, u(t) is the control input (such as external field voltage/current), d(t) is the thermal load disturbance, and y(t) is the keypoint temperature output.

In view of the strong nonlinearity of smart fluid viscosity changing with temperature, the Arrhenius-type empirical formula was used for fitting, and a correction factor was introduced to compensate for the shear thinning effect [11]. The boundary condition of the microchannel wall is set as a non-uniform heat flux boundary to simulate the hot spot distribution on the chip surface. The

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inlet boundary is set as a pressure inlet or velocity inlet, while the outlet meets the pressure outlet condition for fully developed flow.

3. Optimization strategy

As shown in Figure 2, in order to achieve accurate tracking of chip junction temperature and minimize drive energy consumption, firstly, based on the discrete-time state space model established above:

$$x(k+1) = Ax(k) + Bu(k) + B_d d(k) \tag{3}$$

$$y(k) = Cx(k) \tag{4}$$

Here, $x(k) \in R^n$ is the system state vector, $u(k) \in R^m$ is the control input, $y(k) \in R^p$ is the output variable, and d(k) is the unmeasured thermal load disturbance.

The core of the control is to construct a target functional J(k) in finite time domain. By weighing the tracking error and the control increment, the oscillation of the system is suppressed and the power consumption is reduced. The quadratic objective function is defined as follows.

$$J(k) = \sum_{i=1}^{N_p} \left| y(k+ik) - r(k+i) \right|_Q^2 + \sum_{i=0}^{N_c-1} \left| \Delta u(k+ik) \right|_R^2 \tag{5}$$

Where, N_p is the prediction time domain and N_c is the control time domain.

Based on the above constraints, using the state equation recursion, the output vector Y in the prediction time domain can be expressed as a linear combination of the initial state x(k) and the control increment sequence ΔU :

$$Y = Fx(k) + \Phi\Delta U \tag{6}$$

Where F and Φ are the predicted state matrix and the control matrix, respectively. Substituting the objective function and combining the constraints, the original problem is transformed into a standard quadratic programming problem:

$$\min_{\Delta U} \frac{1}{2} \Delta U^T H \Delta U + G^T \Delta U \tag{7}$$

$$\text{s.t. } M\Delta U \leq \gamma \tag{8}$$

Where $H = \Phi^T Q \Phi + R$ is the Hessian matrix. At each sampling time k, the QP problem is solved efficiently by the interior point method or the effective set method to obtain the optimal control increment sequence ΔU^* . Only the first element $\Delta u^*(k)$ in the sequence is applied to the system, and the above process is repeated at the next time k+1. This "rolling optimization" mechanism gives the system strong anti-interference ability and robustness.

We design a state estimator based on Luenberger observer [12] to reconstruct the state of the system in real time as follows.

$$y_{corr}(k+ik) = y_{pred}(k+ik) + h(k) \tag{9}$$

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Where $h(k) = y_{meas}(k) - y_{model}(k)$ is the measured error at the current time.

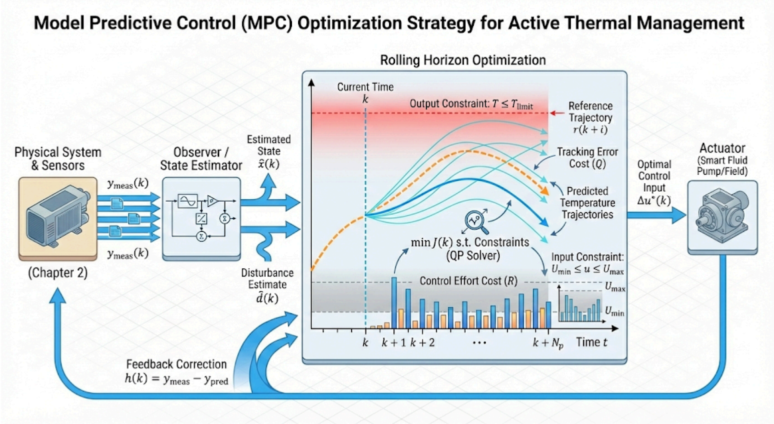

Figure 2. Schematic diagram of the optimization strategy

4. Simulation experiments and results analysis

In order to reproduce the real physical process of "flow-thermo-control" multi-physical field coupling, COMSOL was used to solve PDEs and output the flow field and temperature field distribution in real time [13]. Simulink acts as the control center to run the MPC optimization algorithm [14] and realize bidirectional data interaction through the Level-2 S-Function interface [15].

The simulation object is set as a typical microchannel heat sink structure, and the dielectric nanofluid which is sensitive to electric field is selected as the fluid working medium. The key physical parameters and control parameters are shown in Table 1.

Table 1. Key physical parameters and controller Settings of the simulation system

Category	Parameter	Value	Unit
Geometry	Hydraulic diameter of microchannel	200	μm
	Chip heating area	10×10	mm^2
Properties	Thermal conductivity of fluid	0.6+0.002T	W/(m·K)
	Zero-field viscosity	1.5×10^{-3}	Pa·s
Control	Sampling time	10	ms
	Prediction horizon	20	steps
	Control horizon	5	steps
	Weight matrix	diag(10^4,10^{-2})	-

As shown in Figure 3, for the typical "step load" condition of high-power electronic devices, the experimental results show that the MPC strategy, by relying on its feedforward prediction mechanism, has already calculated the optimal control increment through rolling optimization before the thermal wave reaches the monitoring point, and adjusted the fluid driving field strength in advance. The adjustment time of MPC system is only 0.35s, which is 70.8% shorter than the 1.2s of PID control.

Due to the explicit introduction of state constraints in the objective function, MPC strictly controls the temperature overshoot within 0.5 ° C, while PID control shows overshoot up to 4.5 ° C in the face of large lag links, which can easily trigger the thermal protection mechanism of the chip in practical applications.

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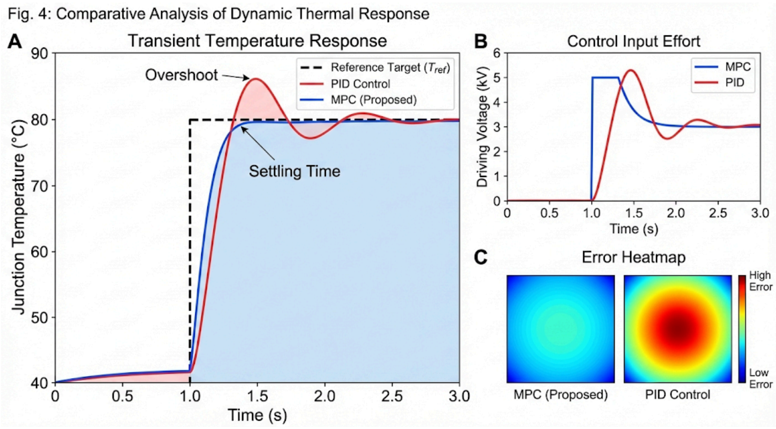

Figure 3. Temperature response curves of MPC and PID controller

As shown in Figure 4, in addition to the temperature control accuracy, the energy efficiency ratio of the system is another core index to evaluate the active thermal management system. By solving a constrained quadratic programming problem, MPC can dynamically find the "minimum action path" of the driving voltage under the premise of maintaining the chip temperature at a safe threshold in the long-period operation test under variable load. The data show that the average power consumption of MPC is reduced by 24.6% compared with the PID strategy, which has to maintain a high flow rate to suppress overshoot.

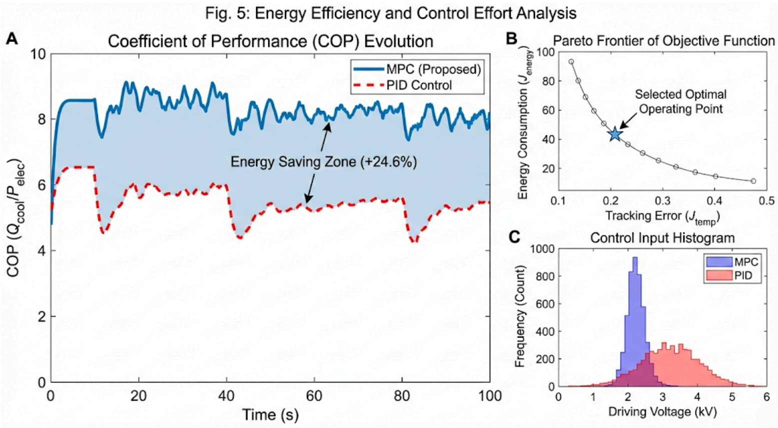

Figure 4. System energy efficiency ratio

In order to verify the control stability under model mismatch, fluid viscosity error and contact thermal resistance disturbance are artificially introduced into the simulation model. The results show that the MPC system exhibits excellent robustness thanks to the real-time feedback correction of the state observer. Although the regulation time is slightly extended, the steady-state error always converges to zero.

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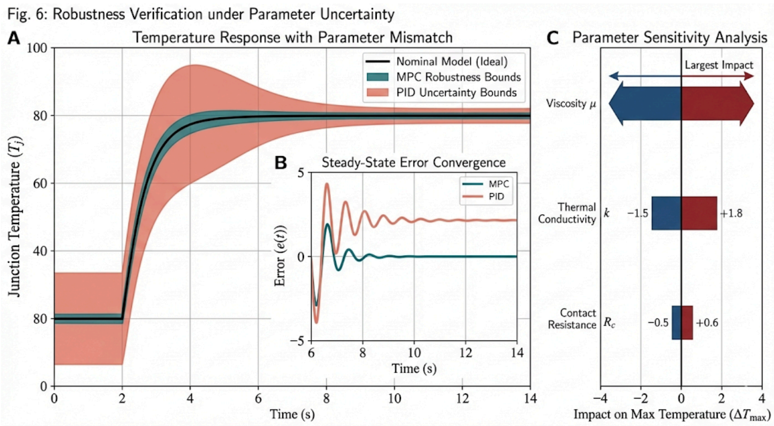

Figure 5. Control stability

5. Conclusion

This paper systematically expounds the control strategy of intelligent fluid in the field of active thermal management. Through the architecture of active thermal management system based on intelligent fluid drive, it verifies the unique advantages of multi-physics coupling drive in solving the problem of nonlinear heat transport. The research shows that the optimization strategy based on MPC not only effectively overcomes the inherent hysteresis characteristics of the fluid system, but also minimizes the drive energy consumption under the premise of ensuring the thermal safety of the device. This result provides a solid theoretical support for the construction of efficient, compact and intelligent electronic cooling systems.

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