FOG-CLOUD MUHITIDA VAZIFALARNI O'TKAZISH VA RESURSLARNI TAQSIMLASHNING GIBRID MODELI

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Annotatsiya. *Fog-cloud muhitida vazifalarni o'tkazish va resurslarni taqsimlash uchun taklif etilgan GRU–DCO–APOA modeli tahlil qilingan. E'lon qilingan tajriba natijalari bo'yicha nisbiy samaradorlik va statistik ahamiyatlilik hisoblanib, modelni takomillashtirish bo'yicha uchta taklif – gisterezisli bo'sag'a, bashoratchilar ansambli va ishonch mezonli maqsad funksiyasi – asoslangan.*

Kalit so'zlar: *fog-cloud hisoblashlari, vazifalarni o'tkazish, resurslarni taqsimlash, yuklamani bashorat qilish, GRU, metaevristik optimallashtirish, APOA.*

Abstract. *The GRU–DCO–APOA model for task offloading and resource allocation in fog-cloud environments is analyzed. Relative efficiency and statistical significance are calculated from published experimental data, and three improvements are substantiated: a hysteresis threshold, an ensemble of load predictors, and a trust-aware objective function.*

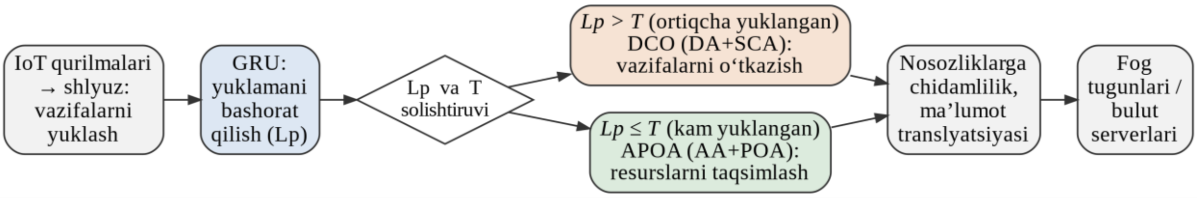
Keywords: *fog-cloud computing, task offloading, resource allocation, load prediction, GRU, metaheuristic optimization, APOA.*

Buyumlar interneti qurilmalari sonining o'sishi markazlashgan bulutli hisoblashning cheklovlarini namoyon etmoqda: ma'lumotlarni uzoqdagi markazga uzatish kechikish va energiya sarfini oshiradi [1]. Gibrid fog-cloud arxitekturasida kechikishga sezgir vazifalar fog tugunlarida, murakkab vazifalar esa bulutda bajariladi. Bunda asosiy masala – vazifani qaysi tugunda bajarishni hal qilish (*task offloading*) va tugun resurslarini taqsimlash bo'lib, u kechikish, energiya, xarajat va yuklama muvozanatini birgalikda hisobga oluvchi NP-murakkab ko'p mezonli masaladir [2]. Mavjud ishlarning katta qismi bu ikki masalani alohida yechadi va tugun yuklamasiga reaktiv javob beradi.

Ameena va Loganthan [3] ushbu kamchiliklarni bartaraf etuvchi modelni taklif etgan: tugun yuklamasi L_p GRU tarmog'i bilan bashorat qilinadi va bo'sag'a T bilan solishtiriladi; $L_p > T$ bo'lganda Drawer algoritmi va sinus-kosinus algoritmi birlashmasi – DCO [4, 5] yordamida vazifalar boshqa tugunlarga o'tkaziladi, aks holda kamondan otish va pufferbaliq algoritmlari birlashmasi – APOA [6, 7] orqali tugunga qo'shimcha resurs ajratiladi (1-rasm). Har ikkala bosqichda nomzod yechim energiya sarfi E, bashorat qilingan yuklama L_p, makespan M va xarajat C ni birlashtiruvchi moslik funksiyasi bilan baholanadi:

$$\Phi = \alpha\hat{E} + \beta\hat{L}_p + \gamma\hat{M} + \delta\hat{C}, \qquad \hat{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \qquad (1)$$

bu yerda $\alpha + \beta + \gamma + \delta = 1$ – vazn koeffitsiyentlari, $\hat{x}$ – min-max normallashtirish.



1-rasm. GRU–DCO–APOA modelining umumiy sxemasi ([3] asosida tuzilgan)

Modelning e’lon qilingan natijalari mustaqil ravishda qayta baholandi. APOA ning b-usulga nisbatan nisbiy ustunligi $\Delta = (x_b - x_\mathrm{A})/x_b \cdot 100$ % sifatida, statistik ahamiyatlilik esa $k = 9$ qatlamli kross-validatsiya bo‘yicha o‘rtacha qiymat μ va standart og‘ish s asosida Koen effekt o‘lchami d va Uelch t-mezoni orqali hisoblandi ($n = 9$):

$$d = \frac{\mu_b - \mu_\mathrm{A}}{\sqrt{(s_b^2 + s_\mathrm{A}^2)/2}}, \qquad t = \frac{\mu_b - \mu_\mathrm{A}}{\sqrt{(s_b^2 + s_\mathrm{A}^2)/n}}. \qquad (2)$$

Hisoblash natijalari 1-jadvalda keltirilgan; taqqoslashda eng kuchli muqobil usul – aktor-kritik chuqur Q-o‘rganishga asoslangan H-DQAC [8] olingan.

1-jadval

APOA ning eng kuchli muqobil usulga (H-DQAC) nisbatan ustunligi

Ko‘rsatkich	**Δ, % (100 vazifa)**	**Δ, % (300 vazifa)**	**Δ, % SACO ga nisbatan**	***d***	***p***
Energiya sarfi	1,9	3,1	32,8	0,25	0,60
Bashorat qilingan yuklama	9,8	6,4	85,6	0,22	0,65
Bajarilish vaqti	26,1	15,4	73,9	0,69	0,16
Makespan	2,4	4,4	47,7	0,36	0,45

Izoh: SACO ga nisbatan Δ – 100 ta vazifa uchun; d, p – H-DQAC bilan solishtirish ($n = 9$). [3] ma’lumotlari asosida hisoblangan.

Natijalar ikki xulosani ko‘rsatadi. Birinchidan, klassik to‘da algoritmlariga nisbatan APOA ustunligi katta va barqaror (SACO bilan solishtirganda $d = 3{,}2$–$10{,}4$, $p < 0{,}001$). Ikkinchidan, zamonaviy usullarga nisbatan ustunlik kichik: energiya va makespan bo‘yicha farq 2–4 % bo‘lib, standart og‘ishdan ancha kam (energiya uchun ±0,08 J, ya’ni o‘rtacha qiymatning 22 % i), va hech bir ko‘rsatkichda farq 0,05 darajada statistik ahamiyatli emas. Bajarilish vaqti bo‘yicha ustunlikni tasdiqlash uchun har bir usulga kamida 34 ta, energiya bo‘yicha esa 250 dan ortiq mustaqil ishga tushirish talab etiladi. Bundan tashqari, natijalar faqat simulyatsiyada va 13 tugunli topologiyada olingan; “bepul tushlik yo‘q” teoremasiga [9] ko‘ra bunday ustunlik masala sinfiga bog‘liq.

Tahlil asosida modelni takomillashtirishning uchta yo‘nalishi taklif etiladi. Birinchidan, yagona statik bo‘sag‘a yuklama T atrofida tebranganda vazifalarning qayta-qayta o‘tkazilishiga olib keladi; buning oldini olish uchun ikki bo‘sag‘ali gisterezis qoidasi qo‘llanilishi, ya’ni tugun $L_\mathrm{p} > T_\mathrm{H}$ da ortiqcha yuklangan, $L_\mathrm{p} < T_\mathrm{L}$ da kam yuklangan, oraliq holatda esa barqaror hisoblanib, optimallashtirish ishga tushirilmasligi lozim. Ikkinchidan, bashoratchining ustunligi rejimga bog‘liq (energiyani bashorat qilishda GRU xatoligi 0,127, LSTM niki 0,289; sirpanuvchi oyna tahlilida esa teskari nisbat), shu sababli bashoratchilar ansambli yoki ularni joriy xatolik bo‘yicha dinamik tanlash maqsadga muvofiq.

Uchinchidan, modelda xavfsizlik optimallashtirish mezonlariga kiritilmagan, holbuki vazifani buzilgan tugunga o‘tkazish ma’lumotlar maxfiyligiga tahdid soladi, yuklama haqida soxta ma’lumot yuborish esa bashoratni buzib, vazifalarni hujumchi tuguniga yo‘naltirishi mumkin. Shu bois maqsad funksiyasiga tugunning ishonch darajasi $\tau_j \in [0, 1]$ kiritilishi taklif etiladi:

$$\Phi' = \alpha\hat{E} + \beta\hat{L}_{\mathrm{p}} + \gamma\widehat{M} + \delta\hat{C} + \eta\left(1 - \tau_j\right), \qquad \alpha + \beta + \gamma + \delta + \eta = 1, \quad (3)$$

bu yerda τ_j tugunning autentifikatsiya holati, bajarish tarixi va anomaliyalarni aniqlash tizimi baholari asosida hisoblanadi; ishonch darajasi minimal qiymatdan past tugunlar nomzodlardan chiqariladi.

Xulosa. GRU–DCO–APOA modeli yuklama bashorati va ikki bosqichli gibrid optimallashtirishni birlashtirgani bilan ahamiyatli, biroq uning zamonaviy usullarga nisbatan ustunligi mavjud tajriba tanlamasida statistik tasdiqlanmaydi. Taklif etilgan gisterezisli boshqaruv, bashoratchilar ansambli va ishonch mezonli maqsad funksiyasi modelning barqarorligi va xavfsizligini oshirish imkonini beradi; ularni eksperimental tekshirish keyingi tadqiqot yo‘nalishi hisoblanadi.

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