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ДОДАТОК А
СПИСОК ПУБЛІКАЦІЙ ЗДОБУВАЧА ЗА ТЕМОЮ ДИСЕРТАЦІЇ

Наукові праці, в яких опубліковано основні наукові результати:

1. Бабуджан Р., Ісаєнков К., Красій Д., Водка О., Задорожний І., Ющук М. Використання методів машинного навчання для бінарної класифікації робочого стану підшипників за сигналами їх віброприскорення. Вісник Національного технічного університету «ХПІ». Серія: Системний аналіз, управління та інформаційні технології. 2021. № 2 (6). С. 15–22. DOI: https://doi.org/10.20998/2079-0023.2021.02.03. (Б).

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