工业化的兴起导致了对能源的大量需求，化石能源的枯竭和环境污染促进了新能源的兴起[1-3]。然而，大多数可再生能源，如太阳能和风能，本质上是间歇性的，依靠自然现象发电，此时储能成为一种新的需求[4-10]。可充电锂离子电池作为一种储能技术，因其密度高、容量大、寿命长等优点而得到广泛应用[11,12]。然而，广泛使用也带来了电池寿命、电量不足、电池爆炸等问题，如图1所示。如果能够在电池老化之前预测电池寿命，就可以避免上述问题，并且可以加快电池开发周期，可以验证新工艺，并且可以对电池进行再循环[13-15]，这将为电池的制造、使用和优化带来重大机遇[16-18]。

目前，用于电池寿命估算的模型主要可分为等效电路模型（ECM）[19-20]、电化学模型[21-23]和数据驱动模型[24-29]。电化学模型和等效电路模型的精度和鲁棒性有限，因此这两种模型都不是一个好的可行解。相比之下，数据驱动的模型不需要了解电池内部复杂的化学反应，没有复杂的过程来构建电路，其他优点被研究人员广泛使用。同时，随着近年来研究的发展，发现电池数据集中的噪声是不可避免的，这主要是由于充放电过程中的环境干扰，如温度变化和湿度波动。此外，实验条件并不能完全模拟现实，因此越来越多的研究开始关注带噪声的电池寿命预测。

线性参数估计问题出现在信号处理等广泛的科学学科中[30-31]。如[32]和[33]所示，当所有感兴趣的变量都具有参数线性关系并且所有测量值都受到噪声污染时，总最小二乘法是参数估计的最佳选择。 然而，在实际情况下，电池制造商提供的电池信息数据集来自不同的来源，因此温度、人为干扰和传感器造成的误差差异很大。此时，不可能简单地假设数据集的噪声服从相同的分布，直接使用TLS/OLS并不能建立良好的电池寿命预测模型。因此，本文对电池寿命线性模型的建立进行了改进， 在对具有不同噪声分布的电池样本进行加权后，使用TLS/OLS进行预测。通过循环迭代可以精确计算出噪声分布的标准差，并建立适应不同噪声分布的预测模型来预测电池寿命。预测结果表明，该方法优于传统的TLS/OLS方法。

本文基于商用锂离子电池的三个公开数据集，分别由41个、43个和40个样本组成，分别称为“数据集1”、“数据集2”和“数据集3”。尽管这些数据集总共提取了 20 个特征，但我们进一步根据领域专业知识手动选择了 3 个重要特征的子集。具体含义见表1。我们按照 9：1 的比例划分三个数据集，并将它们组合为训练集和测试集。每个实验随机调整样本顺序，每个运行独立地随机生成训练和测试数据集。每种方法报告的中位数为 1,000 个 RMSE，因此误差测量不会受到随机波动的强烈偏差。

如图 3 所示，我们设置了四种不同的噪声比。图a、b、c、d为实验结果随噪声水平的增加而增加：1）随着噪声的增加，TLS和OLS的效果明显变差，而改进算法受噪声水平影响不显著，稳定性强。2）改进算法TLS\_EM和OLS\_EM结合EM IDEA算法比传统算法TLS和OLS效果更好，表明改进算法更适合于有噪声的电池数据集。3）TLS\_EM的效果优于OLS\_EM，TLS的效果也优于OLS）。在所有测量值都受到噪声污染的情况下，TLS比LS具有更大的优势。 图e、f、g、h为增加训练集占比的实验结果：1）随着训练集占比的增加，4种方法效果较好，训练数据越多，模型的预测能力提高。2）无论比例如何 训练集上，改进算法优于传统算法，显示了该算法与EM思想的有效性。3）大多数情况下，训练集占比超过25%）TLS\_EM优于OLS\_EM，说明TLS\_EM比OLS\_EM更适用。图 4 显示了该算法的迭代噪声收敛过程。

本文建立了线性模型来计算电池寿命。对不同噪声分布的电池样本进行加权后，采用TLS/OLS进行预测。通过循环迭代，可以精确计算噪声分布的标准差，同时建立适应不同噪声分布的预测模型来预测电池寿命。结果表明，该方法具有较好的效果。

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