The industrialization revolution led to a large demand for energy, and the depletion of fossil energy and environmental pollution promoted the rise of new energy [1-3]. However, most renewable energy sources, such as solar and wind, are intermittent in nature and rely on natural phenomena to generate electricity, at which point energy storage becomes a new demand [4-10]. Due to their high density, high capacity, and long lifespan, lithium-ion batteries have become the primary energy storage device for portable electronic devices, electric vehicles (EVs), and many other applications[11,12]. However, in the use of lithium batteries, it cannot be ignored that the decline in battery performance will cause problems such as reduced battery life, insufficient power, and battery explosion, as shown in Figure1. If the battery life can be predicted before the battery aging, the above problems can be avoided, and the battery development cycle can be accelerated, new processes can be validated, and the battery can be rerecycled [13-15], which will bring major opportunities for the manufacturing, use and optimization of the battery [16-18].

At present, the models used for battery life estimation can be mainly divided into equivalent circuit model (ecm)[19-20], electrochemical model [21-23] and data-driven model [24-29]. The accuracy and robustness of the electrochemical model and the equivalent circuit model are limited, so these two models are not a good viable solution. In contrast, data-driven models do not need to understand the complex chemical reactions inside the battery, there is no complex process to build the circuit and other advantages are widely used by researchers. At the same time, with the development of research in recent years, it is found that the noise in the battery data set is inevitable, which is mainly due to the environmental interference during the charging and discharging process, such as temperature change and humidity fluctuation. In addition, experimental conditions do not fully simulate reality, so more and more research has begun to focus on the prediction of battery life with noise.

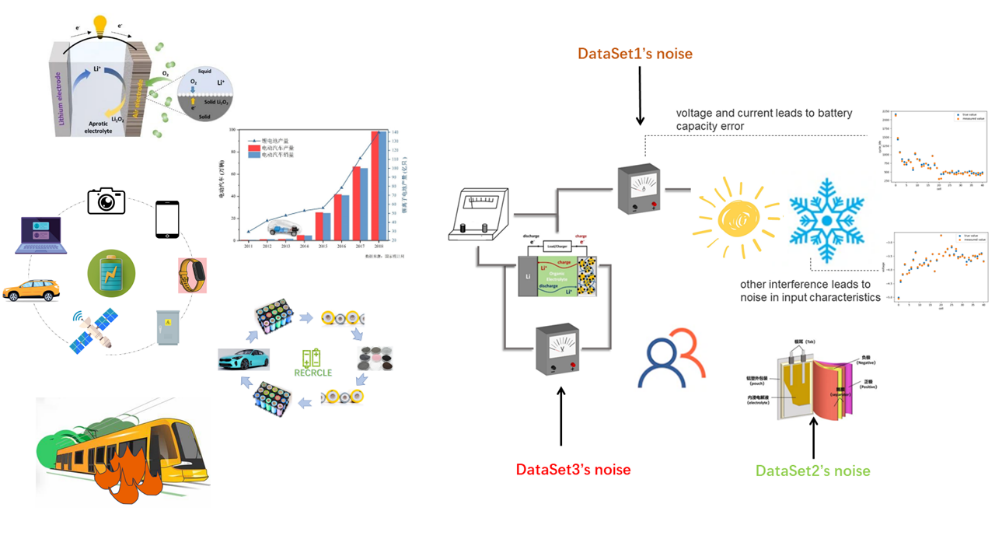


Figure1: Lithium battery applications and hidden dangers

Linear parameter estimation problems arise in a wide range of scientific disciplines such as signal processing [30-31]. As shown in [32] and [33], total least squares is the best choice for parameter estimation when all variables of interest have parametric linear relationships and all measurements are noise polluted.

However, in the actual situation, the battery information data sets provided by battery manufacturers come from different sources, so the errors caused by temperature, human interference and sensors are very different. At this time, it is impossible to simply assume that the noise of the data sets obey the same distribution, and the direct use of TLS/OLS cannot establish a good battery life prediction model. Therefore, this paper made improvements in the establishment of a linear model to calculate battery life. After weighted battery samples with different noise distributions, TLS/OLS was used for prediction. The standard deviation of noise distribution could be accurately calculated through cyclic iteration, and a prediction model adapted to different noise distributions was established to predict battery life. The prediction results show that our method is better than the traditional TLS/OLS method.

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