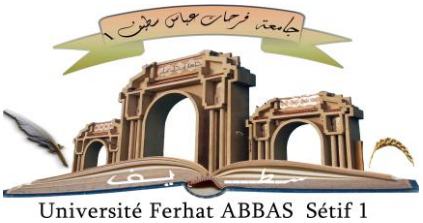
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Ferhat ABBAS University of Setif
Faculty of Sciences



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AI-Driven Dynamic Energy Routing in P2P Energy Systems

A Dissertation presented by

MERZOUGUI Mohamed Amine

HADNA Islam Amir

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Abstract

The rapid evolution of smart grids and the increasing integration of renewable energy resources have transformed traditional electrical networks into decentralized and intelligent energy systems. Peer-to-peer (P2P) energy trading has emerged as a promising paradigm that enables direct energy exchange between distributed producers and consumers, improving renewable energy utilization and reducing dependency on centralized infrastructures. However, efficient energy routing in P2P systems remains a challenging problem due to network complexity, dynamic energy generation, variable demand, and transmission losses. This thesis proposes an artificial intelligence-based approach for dynamic energy routing and power loss prediction in P2P energy systems using Graph Neural Networks (GNNs). The electrical distribution network is modeled as a graph structure where nodes represent households or prosumers and edges represent physical electrical connections. Node and edge attributes, including energy production, consumption, distance, resistance, and network characteristics, are integrated into the learning process. A complete data processing pipeline is developed to transform raw energy consumption and solar generation data into realistic P2P energy transactions with associated physical constraints. A physics-aware Graph Attention Network (GAT) model is designed to learn complex spatial relationships between network components and predict energy routing losses while selecting efficient transmission paths. Experimental results demonstrate that the proposed model achieves accurate power loss prediction and improves routing efficiency compared with traditional approaches. The obtained results highlight the potential of graph-based deep learning techniques as scalable solutions for future intelligent energy networks.

Keywords: Smart Grid, Peer-to-Peer Energy Trading, Graph Neural Network, Graph Attention Network, Energy Routing, Power Loss Prediction.

Résumé

L'évolution rapide des réseaux électriques intelligents et l'intégration croissante des sources d'énergie renouvelables ont conduit à la transformation des systèmes électriques traditionnels vers des architectures décentralisées et intelligentes. Le commerce d'énergie pair-à-pair (P2P) représente une approche prometteuse permettant aux producteurs et consommateurs distribués d'échanger directement de l'énergie, favorisant ainsi une meilleure exploitation des ressources renouvelables. Cependant, le routage efficace de l'énergie dans les systèmes P2P reste un problème complexe en raison de la dynamique des flux énergétiques, des variations de production et de consommation, ainsi que des pertes électriques lors de la transmission. Ce mémoire propose une approche basée sur l'intelligence artificielle pour le routage dynamique de l'énergie et la prédiction des pertes électriques dans les réseaux P2P en utilisant les réseaux de neurones sur graphes (GNN). Le réseau électrique est représenté sous forme d'un graphe où les nœuds représentent les maisons productrices ou consommatrices et les arêtes représentent les connexions électriques physiques. Une chaîne complète de traitement des données est développée afin de transformer les données énergétiques brutes en transactions P2P réalistes intégrant les contraintes physiques du réseau. Un modèle basé sur le Graph Attention Network (GAT) est proposé afin d'apprendre les relations complexes entre les différents éléments du réseau et d'optimiser les chemins de transmission. Les résultats expérimentaux montrent que l'approche proposée permet une prédiction précise des pertes énergétiques et améliore l'efficacité du routage par rapport aux méthodes classiques.

Mots clés : Smart Grid, Energie P2P, Graph Neural Network, GAT, Routage énergétique, Pertes électriques.

ملخص

شبدت أنظمة الطاقة الكهربائية فى السنوات الألأخيرة تطوراً كبيراً نتيجة الألانتشار المتزايد لمصادر الطاقة المتجددة وظهور الشبكات الكهربائية الذكية. وقد أصبح نظام تبادل الطاقة من نظير إلى نظير من الحاول الحديثة الى آسمح للمستبلكين والمنتجين الصغار بتبادل الطاقة مباشرة دون الألاعتماد الكامل على الألأنظمة المركز ية.

رغم ذلك، فإن عملية توجيه الطاقة داخل شبكات نظير إلى نظير تعتبر تحدياً معقداً بسبب تغير الألإنتاج والألاستهلاك، وطبيعة الشبكة الكهربائية، ووجود خسائر أثناء نقل الطاقة.

يقترح هذا العمل منبجية تعتمد على الذكاء الألاصطناعى من أجل التوجيه الديناميكى للطاقة والتنبؤ بالخسائر الكهربائية باستعمال الشبكات العصبية البيانية. تم تمثيل الشبكة الكهربائية على شكل رسم بيانى حيث تمثل العقد المنازل أو الوحدات المنتجة والمستبلكة للطاقة، بينما تمثل الحواف خطوط الربط الكهربائية.

تم تطوير سلسلة معالجة كاملة للبيانات لتحو يل بيانات الألإنتاج والأستهلاك إلى معاملات تبادل نظير إلى نظير واقعية مع احترام القيود الفيز يائية للشبك.ة كما تم تصميم نموذج من أجل تعلم العلاقات المعقدة بين عناصر الشبكة والتنبؤ بالخسائر وتحسين مسارات نقل الطاقة.

أظهرت النتائج التجريبية قدرة النموذج المقترح على التنبؤ الدقيق بالخسائر وتحسين كفاءة التوجيه مقارنة بالطرق التقليدية، مما يبرز أهمية تقنيات التعلم العميق المعتمدة على الرسوم البيانية فى تطوير شبكات الطاقة المستقبلية.

الكلمات المفتاحية: الشبكات الذكية، تداول الطاقة من نظير إلى نظير، الشبكات العصبية البيانية، شبكات الأنتباه البيانية، توجيه الطاقة، التنبؤ بخسائر القدرة .

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Abbreviations

List of Abbreviations

AC : Alternating Current

AI : Artificial Intelligence

ANN : Artificial Neural Network

API : Application Programming Interface

CSV : Comma-Separated Values

DC : Direct Current

DL : Deep Learning

Edge : Connection between nodes in a graph

Epoch : One complete training cycle over the dataset

Feature : Input variable or characteristic

GAT : Graph Attention Network

GCN : Graph Convolutional Network

GNN : Graph Neural Network

GPU : Graphics Processing Unit

Graph : Structure composed of nodes and edges

IEEE : Institute of Electrical and Electronics Engineers

kW : Kilowatt

kWh : Kilowatt-hour

Loss : Loss function measuring prediction error

MAE : Mean Absolute Error

ML : Machine Learning

MSE : Mean Squared Error

Node : Element of a graph representing an entity

P2P : Peer-to-Peer

PCA : Principal Component Analysis

Prediction : Output generated by a model

ReLU : Rectified Linear Unit

$\mathbf{R}^2$: Coefficient of determination

SVM : Support Vector Machine

t-SNE : t-distributed Stochastic Neighbor Embedding

Training : Model learning phase

Validation : Model validation phase

Test : Final evaluation phase

V : Voltage

I : Current

R : Resistance

η : Energy efficiency

$P_{\mathbf{loss}}$: Power loss

E : Energy