

Managing Big Energy Data for (Really) Smart Grids

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Agenda

- Why Big Energy Data?
- What is Big Energy Data?
- What do we do with Big Energy Data?
 - And **how** do we do it?

Why Big Energy Data?

- Societal challenges and solutions
 - Global warming greenhouse gas emission cuts
 - Energy supply security reduce energy purchased from outside
 - Nuclear risks nuclear phaseout
- Solution: more energy from renewable energy sources
 - EU 20-20-20 goals,...
 - DK: 2020: 50% of electricity from RES, 2035: 100% electricity and heat from RES, 2050: 100% RES in all sectors
- Implication: move from fossile to electric energy
 - EVs and heatpumps
 - Danish electricity (not energy) consumption **tripled** in 2050

Uncertainties of Renewables

- Fluctuating Energy
 - Wind power
 - Photo Voltaic
 - Waves / Tides



• Hydro is easy...



14

12

10

8

6 -

4 -2 -0 -

Energy Production [kW]

CRES

22 kWp

(Greece)

Too Much or Too Little Energy

2008 DK West figures

Today (2008)





Recent DK figures for electricity produced by wind, % of total

- December 2013 57.4%
- January-June 2014: 41.2%
- 2014: 39.1%
- The future is here today!

Flexible Demand To The Rescue









- Dishwashers and washing machines can run flexibly
- EVs can be (de-) charged flexibly during parking intervals
- Heatpumps can run flexibly within a comfort temperature interval
- Up to 80-85% of the (tripled) future demand is flexible

Future Vision: Smart Grids

Smart Grids

- Increased flexibility of energy networks via ICT (monitor, control)
- Goals: more RES, active customer involvement, balancing demand/supply



Smart Meter: foundation for smart grids (bi-directional communication)



Data Management Challenges

- Large-Scale Distributed Systems
 - Number of stakeholders, number of of nodes, amount of data
- High Availability / Fault Tolerance
 - Basically available, soft state, eventual consistent
- Near-Realtime Data Synchronization and Integration
 - High update rates, low latency, protocol/schema/format heterogeneity
- Advanced Analytics
 - Time series forecasting
 - Balancing
 - Classification, C
 - Clustering,
 - Association rule mining



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What is Big Energy Data?

- Variety: complex data of many different types
 - Consumption data from smart meters, sockets, and appliances
 - Production data from wind, solar, power plants,...
 - Flexibility data what demand and supply is (how) flexible?
 - Prices, weather, ...
- Volume: a lot of it
 - EU consumption per prosumer per sec: 20+ trillion values/day
 - Then go to sockets/appliances and add the other data types
- Velocity: fast data
 - Real-time smart meter readings
 - So fast it hasn't even happened yet: everything is *(re-)forecasted*
- We will focus on variety today (velocity+volume tomorrow)

The MIRABEL Project

EU FP7 project (call 4) Objective: Novel ICT Solutions for Smart Electricity Distribution Networks

mirabel-project.eu

Timeline: 01/2010 to 04/2013





Consumers (households, SMEs,..) have some flexible,

- schedulable demand
- such as dishwashers, washing machines, EVs, heat pumps, …
- ⇒ specified and treated as **flex-offers (FOs)** with **explicit** flexibility in
 - Time (flexibility interval)
 - Amount of electricity



Use Case: Charging an EV

- A consumer arrives home at 10pm and wants to recharge the electric car's battery at the lowest possible price by the next morning. Completion time is set to 6 am.
- 2. The prosumer node generates an FO
- **3**. Based on weather forecasts, the trader's node schedules the FO to start energy consumption at 3am and sends back a message to the prosumer's node.
- 4. The consumer's node of EDMS starts supplying energy to the electric vehicle at 3am.



Use case: Balancing



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Class specifications referenced through attributes of the FlexEnergy class.					
< <enumeration>></enumeration>	EnergySourceType	PriceConstraint			
FlexEnergyType	+classification: String	+minPrice: Monev[01]			
+PRODUCTION	, , , , , , , , , , , , , , , , , , ,	+maxPrice: Money[01]			
+CONSUMPTION					





Flex-Offer Processing Cycle



Flex-offer Aggregation Overview

- Large set of input FOs aggregated into small set of output FOs
- Disaggregation does the reverse, after macro-level scheduling
- Always possible to correctly disaggregate scheduled flex-offers
- Number of aggregated flex-offers as small as possible
- Loss of flexibility in the aggregation as small as possible
- Aggregation+scheduling+disaggregation within 10 min
- 3-step aggregation (grouping, bin-packing,N-to-1 aggregation)



Forecasting+Scheduling Overview



- Forecasting
 - Transparent forecast model creation/usage/maintenance
 - Support for single and multi-equation models
 - Awareness for external influences, e.g., weather
 - Forecasting for demand, supply, FOs
 - Continuous evaluation and maintenance required
- Scheduling
 - Find best schedule for (agg) FOs, fix start times and energy flex.
 - Forecasted energy production, consumption, and market prices
 - Minimize the evaluation function (cost of imbalances)

$$c(S,M) = \underbrace{\sum_{i=1}^{m} p_{I-}^{i} \left| E_{I}^{i} \right|}_{E_{I}^{i} < 0} + \underbrace{\sum_{i=1}^{m} p_{I+}^{i} E_{I}^{i}}_{C_{I+}} + \underbrace{\sum_{k=1}^{n} \left(\sum_{j=1}^{n_{k}} p_{k}^{j} E_{k}^{j} \right)}_{C_{FO}} + \underbrace{\sum_{i=1}^{m} p_{M-}^{i} \left| E_{M}^{i} \right|}_{E_{M}^{i} < 0} - \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E_{M}^{i}}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M-}^{i} \left| E_{M}^{i} \right|}_{C_{M-}} + \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E_{M}^{i}}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M-}^{i} \left| E_{M}^{i} \right|}_{C_{M-}} + \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E_{M}^{i}}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M-}^{i} \left| E_{M}^{i} \right|}_{C_{M-}} + \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E_{M}^{i}}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M-}^{i} \left| E_{M}^{i} \right|}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E_{M}^{i}}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M-}^{i} \left| E_{M}^{i} \right|}_{C_{M-}} + \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E_{M}^{i}}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E_{M+}^{i}}_{C_{M+}} + \underbrace{\sum_{i=1}^{m} p_{M+}^{i} E$$

Prohibitive to find optimal solution, so approximation used.

Component Interplay and Timing



MIRABEL Distributed System

Reflect the Harmonized Role Model for energy markets



Flex-Offer Storage and Querying

 How to store and query flex-offers and other MIRABEL data in an object-relational data warehouse ?

MIRABEL DW Context



EDMS NODE ARCHITECTURE





- DW accepts many insert/analytical queries from analytical components
- A suitable DW schema is need for efficient query evaluation

Storage Contributions

We:

- Present a generic DW schema supporting all levels of the EDMS hierarchy
- Discuss the complexities of the schema compared to traditional DW schemas
- Discuss alternative data modeling strategies
- Evaluate schema alternatives using typical queries from the MIRABEL project

- More on the MIRABEL EDMS: "Data Management in the MIRABEL Smart Grid System", EnDM 2012
- More on the MIRABEL DW: "Real-time Business Intelligence in the MIRABEL Smart Grid System", BIRTE 2012

MIRABEL DW: Schema

- Based on the MIRABEL data model
 - Common information model (CIM) by IEC
 - Represent major objects in an electric utility enterprise
 - Harmonized Electricity Market Role Model by ebIX[®], EFET and ENTSO-E
 - Define administrative data internally interchanged between European electricity markets

None of the existing models focus on storage of energy-related entities

- Schema is complete for the prototype of the MIRABEL system
- Represents energy data essential in the MIRABEL context
 - Actors of European Electricity Market,
 - Flex-offers,
 - Time series of energy, power, and prices

MIRABEL DW: Actors and Roles



MIRABEL DW: Actors and Roles

- For every actor-role, the schema captures:
 - Time-series
 - Flex-offers



MIRABEL DW: Flex-Offers



MIRABEL DW: Time Series





MIRABEL DW: Complete Schema



MIRABEL DW: Alternative Designs

Flex-offer and timeseries schema alternatives

Denormalized



D_timeSeries

tid	nam e	entityRolel D	typeld	
1	TS1	0	1113	
2	TS2	1	1114	

F_timeSeriesInterval

tid	timeIntervalld	value
1	1000	11.2
1	1001	11.4
2	1000	101.1
2	1001	101.2

F_timeSeries

tid	name	entityRolel d	typeld	 timeIntervall d	valu e
1	TS1	0	1113	1000	11.2
1	TS1	0	1113	1001	11.4
2	TS2	1	1114	1000	101. 1
2	TS2	1	1114	1001	101. 2



MIRABEL DW: Alternative Designs

Flex-offer and timeseries schema alternatives

Array-based



D_timeSeries

tid	nam e	entityRolel D	typeld	•••	
1	TS1	0	1113		
2	TS2	1	1114		
F_timeSeriesInterval					

tid	timeIntervalld	value
1	1000	11.2
1	1001	11.4
2	1000	101.1
2	1001	101.2

tid	name	entityRolel d	typeld	 startTim eInterva IId	valueArray
1	TS1	0	1113	1000	{ 11.2, 11.4 }
2	TS2	1	1114	1000	{ 101.1, 101.2 }



F_timeSeries

MIRABEL DW: Experiments

Experiment setup

- Real energy consumption data: 963 time series, 32.1M values (MeRegio),
- Synthetically generated 3.1M flex-offers
- Standard server machine
 - Linux server with 16 GB RAM, 2x Intel Xeon CPUs, 4 SATA 7200RPM disks
 - PostgreSQL 9.1, tables are "fully vacuumed"
- Queries executed in round-robin fashion 5 times

Flex-Offer Schema Experiments

Flex-offer queries

- Q1: Compute total flexibility per flex-offer
- Q2: Compute sum of all scheduled (fixed) energy
- Q3: Builds a time series that represents amounts of scheduled (fixed) energy

Results

- MDW variant is the fastest
- MDW variant uses optimal amount of space




Time Series Schema Experiments

Time series queries

- Q4:Compute energy balance for 24h considering total demand and supply
- Q5: Find time series with average energy exceeding an average time series by 25%

Results

- MDW variant is the fastest
- MDW variant uses optimal amount of space



MIRABEL DW: Research Directions

- (Future) distribution of DW
 - The schema will be replicated on all nodes of EDMS
 - Node holds only relevant data and of specific granularity



- Challenges
 - Propagation of data through the hierarchy, caching
 - Specialized versions of the schema for different types of nodes such that queries formulated on generic schema can be translated to the specialized schemas

MIRABEL DW: Conclusions



- Designed a generic DW schema for complex energy data
- The schema has a number of interesting complexities
 - Facts about facts
 - Composed non-atomic facts
- The schema can be used by a different nodes of hierarchical system
- Evaluated different alternatives (denormalization, arrays)

Aggregating Flex-Offers

- How to we aggregate and disaggregate flex-offers?
- How do we compose many small units of flexibility into fewer, larger, and more useful units, while retaining most of the flexibility ?

Flex-Object (Generalization)

- Flexibility object (flex-object) represents the usage of a resource (e.g., energy) over time as well as flexibilities



Flex-Object Instance



Flex-Object Database Vision



- The energy management system of the utility company manages a large number of flex-objects
- Flex-object database is needed: •
 - Flex-objects as first-class citizens
 - Dedicated or storing other types of data
 - Supported functionality:
 - Different types of flexibility
 - Complex hierachies such as energy distribution grids
 - Supported queries:
 - Flexibility availability queries min/max amounts available at a time interval
 - Adjustment potential queries distribution of amounts that can be potentially injected into (or extracted from) a given time interval
 - Fixing queries alter the plan based on the amount to inject or extract
 - Scheduling queries instantiates flex-objects to match a time series
 - Flex-object aggregation queries combines "micro" flex-objects into fewer "macro" flex-objects
 - <u>Flex-object disaggregation queries</u> explode an instance of a "macro" flex-object into instances of "micro" flex-offers EGC, January 27, 2015 43

Flex-offer (FO) life cycle Recap





Aggregation

Takes N and produces M flex-objects

Disaggregation

• Takes M and produces N instances of flex-objects

 $M \ll N$



Additional requirements for aggregation and disaggregation:

- Compression and flexibility trade-off requirement
- Aggregate constraint requirement, e.g., to limit "how big" aggregate flex-offers are



- Incremental Update Requirement (for the online scenario)
 - New flex-objects are continuously received
 - Earliest starting time of existing flex-objects are approaching

Need to be able to efficiently integrate changed flex-objects into aggregates



Three solutions presented in the paper:

N-to-1 aggregation

- + Satisfies the amount balance requirement
- Does not satisfy compression/flexibility, aggregate constraint, and the incremental updates requirement
- Loses most of flex-object flexibility

N-to-M aggregation

Based on prior grouping and bin-packing

+ Satisfies compression/flexibility, aggregate constraint requirements

- Does not satisfy the incremental update requirement
- Incremental N-to-M aggregation
 - + Satisfies all requirements

- To aggregate flex-objects, we follow these steps
 - Align profiles (partially instantiate flex-objects)



N-to-1 aggregation

- To aggregate flex-objects, we follow these steps
 - Partition slices if needed



• To aggregate flex-objects, we follow these steps

- Build a new profile by summing all corresponding amounts for each







 Different alignments result in different shapes of profiles and remaining time flexibilities, e.g.,

- As in previous example, tf(f1) = tf(f2) = tf(f3)=3, but tf(fA)=1.

- The idea is to allow alignment such that
- Tf(fA)=min_(f in F){tf(f)}
- Three most important alignments ensuring this property:
 - Start-alignment
 - Soft left-alignment
 - Soft right-alignment



N-to-1 aggregation: Start-alignment

• Start-alignment

Pros

- Spreads out amounts throughout the time extent of all individual flexobjects
- Makes larger amounts available as early as possible

Cons

Might result in very long profiles, which might be inconvenient to handle





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• Soft-right/left alignment

Pros

Short profile with concentrated amounts in the left/right

Cons

- Not always possible to achieve hard left/right alignments
- Amounts are not availabe early in time
- Summary of alignments
 - Time flexibility of an aggregate depends on the flex-object with smallest time flexibility

Disaggregation



- N-to-1 aggregation is conservative
- Disaggregation is feasible for every instances of aggregated flex-objects



• Disaggregation ensure the balance of amounts

- **Grouping:** partition flex-objects into groups based on grouping parameter values being within given thresholds
- **Bin-packing:** further partition each group to satisfy aggregate constraints (count, total min/max,...)
- N-to-1 aggregation: as before, applied on every group



Time Flexibility Tolerance



|5-3|≤ TFT



Earliest Start Tolerance



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Parameter Settings

- The user will choose from a number of meaningful predefined parameter settings
 - Short/long profiles
 - Amount as early as possible
 - ...

Incremental N-to-M aggregation

Main contribution

- Incremental grouping
- Incremental optimization
- Incremental bin-packing
- Incremental N-to-1 aggregation



Incremental N-to-M aggregation





Evaluation of the incremental N-to-M aggregation

- A synthetic flex-object dataset from the Mirabel project
- PC with Quad Core Intel R Xeon R E5320 CPU, 16GB RAM, OpenSUSE 11.4 (x86 64)

Scalability Experiment

Variable Parameters

- Flex-object count: 50k ... 1000k
- Grouping parameters
 - EST = 0, 250
 - TFT = 0, 6
- BP: enabled, disabled

Fixed Parameters

 BP ensures aggregated flexobjects with at least 2 hours of time flexibility





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Incremental Behavior

Variable Parameters

 Number of inserts/deletes: 500..256k

- Flex-object count: 500k
- BP: disabled
- Grouping parameters
 - EST = 0
 - TFT = 0



Comparison w. partial baselines (grouping only, non-incremental)

Variable Parameters

- Flex-object count: 50k ... 1000k
- Partial baselines
 - 1. Hierarchical clustering
 - 2. Similarity Group By (Silva, et al.)

- BP: disabled
- Grouping parameters
 - EST = 250
 - TFT = 6





Grouping Parameter Effect

Variable Parameters

- Grouping Parameters
 - EST
 - TFT

- Flex-object count: 500k
- BP: disabled



Group optimization phase effect

Variable Parameters

- Flex-object count: 50k ... 1000k
- Group optimization phase: enabled, disabled

- BP: disabled
- Grouping parameters
 - EST = 0
 - TFT = 6







Bin-packing effect

Variable Parameters

- Flex-object count: 50k ... 1000k
- BP: enabled, disabled



- BP ensures aggregated flex-object with at least 2 hours of time flexibility
- Grouping parameters


Aggregation Conclusions

- Flex-objects allows planning of various processes, e.g., energy use
- A database handling flex-objects is needed
- Aggregation and disaggregation are two most important operations/queries
- Presented 3 aggregation techniques
- Experiments with the incremental N-to-M approach
 - Compression and performance of aggregation depends on grouping parameters
 - Aggregation and disaggregation can be done in linear time (BP-off)
 - When flex-object change marginally, incremental aggregation allows saving lots of aggregation time
 - Optimization step is effective
 - Grouping step is as fast as efficient non-incremental baselines

Aggregation Future Work

- Design the components of the flex-object database
 - Flex-object storage
 - Visualization
 - Techniques to process queries
 - Techniquse to optimize queries
- Support other types of flexibility

>Flex-Offer Aggregation Experiment

Situation today:

- BRP buys energy 24 hours in advance
- > BRP is responsible for imbalances
- Imbalances are penalized

Our additions/scenario:

- Smart-grid CPS is introduced
- 1 household defines 1 flex-offer
- Flex-offers used for consumption corrections
- Flex-offers are available 1 hour before delivery
 - > 10 minutes for *scheduling*
 - > 50 minutes for *aggregation+disaggregation*

+

Experiment

C =

- Generate 100k flex-offers based on real data
- Use real energy prices from Slovenia
- Day ahead schedule has "correct amount", but amount is "incorrectly distributed"

BRP minimizes the cost function:





+



Cost of energy to be bought or

sold on the market



Flex-Offer Aggregation Experiment

THE EFFECTS OF FLEX-OFFER-BASED BALANCING

BRP costs with and without aggregation (reduce^A) while varying grouping parameter values (1000 EUR)



MIRABEL Prototype



Balancing electricity supply and demand in near real-time



MIRABEL In action



MIRABEL Experimental Results

- 7-13% BRP cost reduction
- 13-50% peak-load reduction
- Increase of base-load
- Improving RES integration significantly
 - 70% of the negative impact of fluctuating renewables can be neutralized if 15% of the energy consumption is flexible and intelligently controlled by the BRP.
- Households can reduce energy **bills** by 10-20%.
- With energy storage: up to 50% **CO²** reduction
- Aggregation+scheduling better+faster than just scheduling
- Even better with less conservative flexibility assumptions

Ongoing Project: Totalflex

- "The vision of TotalFlex is to develop a cost-effective, market-based system that utilizes total flexibility in energy demand and production, taking balance and grid constraints into account"
- <u>www.totalflex.dk</u>
- Extending MIRABEL downwards into the home...
 - Home automation integration: device level measurements/control
 - Prediction of consumption/flexibility at *device* level: auto-gen Fos
- ...and **outwards** to capture more aspects
 - More advanced FO aggregation and analysis
 - Modeling heatpumps, etc., as FOs
 - Balancing demand and supply in more aspects
 - Help DSO distribution grid management, e.g., avoid congestions

Totalflex Balance Aggregation

- Initial flex-offer aggregation considers:
 - Only the **market** dimension
 - Not the **physical grid** dimension
- A large flex-offer can violate local capacity constraints
 - Perhaps in combination with other flex-offers
 - Example: charging several EVs in a single street not enough spare capacity
 - Can cause black-out (too little power, frequency drops)
 - Reverse example: getting excess solar power out of a rural area
 - Can cause white-out (too much power, frequency rises)
- Observation
 - Supply and demand can (partly) cancel out each other locally
- Idea:
 - Aggregate flex-offers together to achieve (local) balance

Flex-offers



Positive – Negative



Mixed flex-offer



Flexibility loss example



Why do we aggregate flex-offers?

- Trade on the market macro flex offer
- Reduce the planning complexity
- Stable electricity grid
- Handle imbalances
- Provide anonymity

Balance aggregation - Input



Balance aggregation - Grouping

Energy

+



Balance aggregation - Aggregate



Balance aggregation example



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Simple greedy approach

- Pick largest (negative) flex-offer of the group, f_min
- balance = GetBalance(f_min)
- Iterate within the group
 - Pick the f with balance equal/closest to –balance
 - Aggregate with the currently aggregated
 - Update balance
 - Stop when balance is no longer reduced
- Start again in the same way

Exhaustive greedy approach

- Pick largest (negative) flex-offer of the group, f_min
- balance = GetBalance(f_min)
- Iterate within the group
 - Try all combinations
 - Pick the ONE that reduces the absolute balance the most
 - Update balance
 - Stop when balance is no longer reduced
- Start again in the same way

4 experimental setups

- 1st setup
 - Profiles from 2.5 to 7.5 hours long (production and consumption)
 - Time flexibility from 1 to 3 hours (production and consumption)
- 2nd setup
 - profiles are from 2.5 to 7.5 hours long (consumption)
 - Double length profiles for consumption
 - Half number for production flex offers
 - Same time flexibility between production and consumption
- ^{3rd} setup
 - profiles are from 2.5 to 7.5 hours long (consumption)
 - Double length for production
 - Half number for production flex offers
 - Less time flexibility for production
- ^{4th} setup
 - profiles are from 2.5 to 7.5 hours long (consumption)
 - More than double length profiles for production
 - Half number of production flex offers
 - Less time flexibility for production
 - Less energy flexibility for production

Absolute balance results



Flexibility loss results



Aggregated flex-offers counts



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Execution time results



Balance Aggregation Summary

- Balance aggregation is feasible
 - We can achieve low balance (if possible)
- However, there is a tradeoff
 - Between balance, flexibility loss and processing time
- To get good balance
 - Sacrifice some time flexibility
 - Use more processing time
- The best technique depends on the scenario
 - For some scenarios, start aligment works well
 - For others, simple/exhaustive greedy works better

Totalflex Flexibility Forecasting



Flexibility Detection Study

- Initial study
 - Flexibility analysis and detection in device level data
 - Based on the North American REDD dataset
 - Totalflex device level data (smart sockets) being collected s
- Analysis on device level energy consumption.
- Device flexibility analysis.
- Users' device operation behaviors and patterns.
- A comprehensive device level analysis of energy consumption data.
 - Which will form the foundation for accurate flex-detection, flexprediction, load-prediction.

REDD Data Collection





The REDD hardware architecture for data collection (adapted from REDD [4]).

Background

- Flexibility is in two dimensions:
 - Flexibility in energy profile.
 - Flexibility in time scheduling.

Flexibility: the amount of energy and the duration of time to which the device energy profile (energy flexibility) and/or activation time (time flexibility) can be changed."

Background





Energy demand and supply, before and after demand flexibility management (using flex-offer).

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Background

 TotalFlex¹ project, implements a mechanism to express and utilize the notion of flexibility, using the concept of flexoffer².



¹Totalflex Project, www.totalflex.dk/Forside/ ²flex-offer, proposed in EU FP7 project MIRABEL, www.mirabel-project.eu

Device Operation Properties

- 1) There exists detectable Intra-day and Inter-day patterns in device operation.
 - (a) Weekend and Weekdays patterns are different.
 - (b) Houses exhibit general and specific intra-day and interday patterns.
- 2. There exist time and energy flexibility in device operation.
 - (a) A major percentage of energy consumption comes from flexible devices.
 - (b) An alteration in device energy profile is feasible.
 - (c) Device activation time can be shifted by some duration.
- 3. Some devices are correlated
 - (a) Highly correlated device are operated simultaneously or just after one another.
 - (b) There is some fixed sequence of device operation.

Dataset



- REDD[4] dataset
 - April to June, 2011.

House Number	Days Span	#Days	#Channels	#Devices
House 1	36	35	18	11
House 2	34	15	9	9
House 3	44	23	20	13
House 4	48	30	18	12
House 5	44	9	24	15
House 6	23	18	15	11

Data details for each house.

Device Categorization



 Evaluate devices based on the cost and benefit of utilizing it under the TotalFlex scenario.

Cost: The loss of user-perceived quality caused by accepting flexibility. (for consumers)

Benefit: The available time and energy flexibility for the device.(for energy supplier)

Device Categorization



- Categorization of devices in to three different *flex-categories*
 - Fully-flexible : High benefit at low cost
 - Semi-flexible : Benefit and cost are comparable
 - Non-flexible : Low benefit and high cost

Fully-Flexible	Semi-Flexible	Non-flexible
Dishwasher	Furnace	Bathroom_gfi
Electric_heat	Microwave	Miscellaneous
Refrigerator	Stove	Electronics
Washer_dryer	Oven	Kitchen_outlets
		Lighting

Device flex-categorization
Preprocessing

Aggregation Granularity

Aggregate data into the time granularity that we target for



Data Pre-Processing Steps

Time Series Data

Spike Removal

Distribution over various devices



Distribution Over Flexibility Types



Min, Avg, and Max power Consumption



Distribution Over Days



Weekdays Vs Weekends Distribution



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Distribution of Hourly Device Operations



Daily Operation Frequency



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Device Correlations



Device1	Device2	Frequency	Device1	Device2	Frequency
Oven	Washer dryer	2	Washer dryer	Oven	2
Oven	Microwave	8	Microwave	Oven	9
Oven	Electric heat	1	Electric heat	Oven	1
Dishwasher	Oven	1	Oven	Dishwasher	0
Dishwasher	Washer dryer	2	Washer dryer	Dishwaser	3
Dishwasher	Microwave	2	Microwave	Dishwasher	10
Dishwasher	Stove	1	Stove	Dishwasher	0
Washer dryer	Microwave	12	Microwave	Washer dryer	10
Washer dryer	Electric heat	1	Electric heat	Washer dryer	1
Microwave	Electric heat	8	Electric heat	Microwave	4
Microwave	Stove	6	Stove	Microwave	2
Electric heat	Stove	4	Stove	Electric heat	2
Stove	Oven	1	Oven	Stove	0

Operation sequence for pairs of devices (house 1).

Operation Properties Revisited

- 1) There exists detectable Intra-day and Inter-day patterns in device operation.
 - (a) Weekend and Weekdays patterns are different. \checkmark
 - (b) Houses exhibit general and specific intra-day and interday patterns.
- 2. There exist time and energy flexibility in device operation.
 - (a) A major percentage of energy consumption comes from flexible devices.
 - (b) An alteration in device energy profile is feasible. \checkmark
 - (c) Device activation time can be shifted by some duration $\sqrt{}$
- 3. Some devices are correlated
 - (a) Highly correlated devices are operated simultaneously or just after one another X
 - (b) There is some fixed sequence of device operation. \checkmark

Flexibility Study Summary

- Significant percentage of the total energy demand for a house can be considered to provide flexibility.
- Repeating inter-day and intra-day, house-specific or general patterns across houses.
- Potential of extracting time flexibility.
- Potential of extracting energy flexibility.
- There exist interesting correlations and sequences between device operation.
- Patterns and periodicities for device operation can be detected and predicted, even in stochastic environments.

Flexibility Study Conclusion



- User's possess flexibility in their usage patterns.
- These flexibility can be extracted with low loss of user perceived quality.
- Support the concept of the TotalFlex project of utilizing flexibility for demand management.

Future Work

- 1. Design models for flexibility- and load prediction.
- 2. Econometric analysis of flexibility.
- 3. Generation of flex-offers.

Ongoing Project: Arrowhead

- Collaborative automation
 - Equipment, people, and IT services work together to optimize
 - Largest EU FP7 project
 - FOs as the basis for a Virtual Market of Energy
 - Generic service-oriented architecture for optimal integration
 - Demonstrators/trials for residential buildings, commercial buildings, industrial processes, electromobility (EVs)
 - www.arrowhead.eu

Ongoing and Future Work

- Constraint aggregation
 - Aggregate flex-offers so that they respect grid constraints
- Demand forecasting at device level
 - Challenge of stochastic behavior
- Flexibility detection
 - Extracted from device level forecasts
 - Challenge to estimate available flexibility
- Flexibility prediction
 - What flexibility will be available tomorrow
 - Learn the behavior of users and their flexible devices
- Flex-offer generation
 - Based on predicted flexibilities
- Markets and tax schemes for flexibility
- Integration in devices and systems of systems

Big Energy Data Summary

- Why?
 - CO2 reductions, more renewable energy sources
 - Make (flexible) demand meet (renewable) supply
- What is it?
 - Time series of demand and supply
 - Flex-offers: generalized and explicit energy flexibilities
- What do we do with it?
 - (Repeated) Forecasting, scheduling, ...
 - Storage and querying in a DW
 - Aggregation (incremental, balance)
 - Flexibility detection and extraction
- Bottom line
 - Many data management challenges
 - Some domain specific, some general
 - Join the fun ☺

Key References

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