Evolving Needs and Use of Forecasting on the Evolving Power Grid

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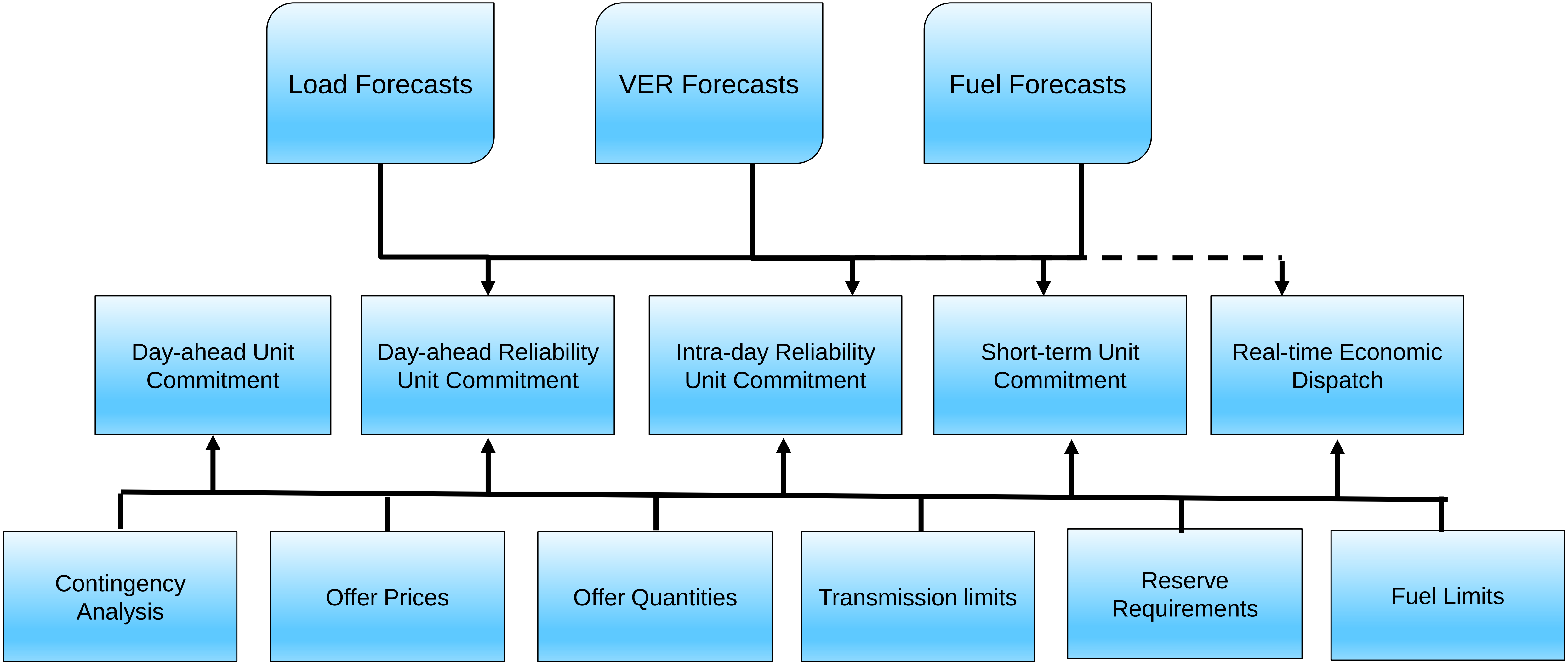
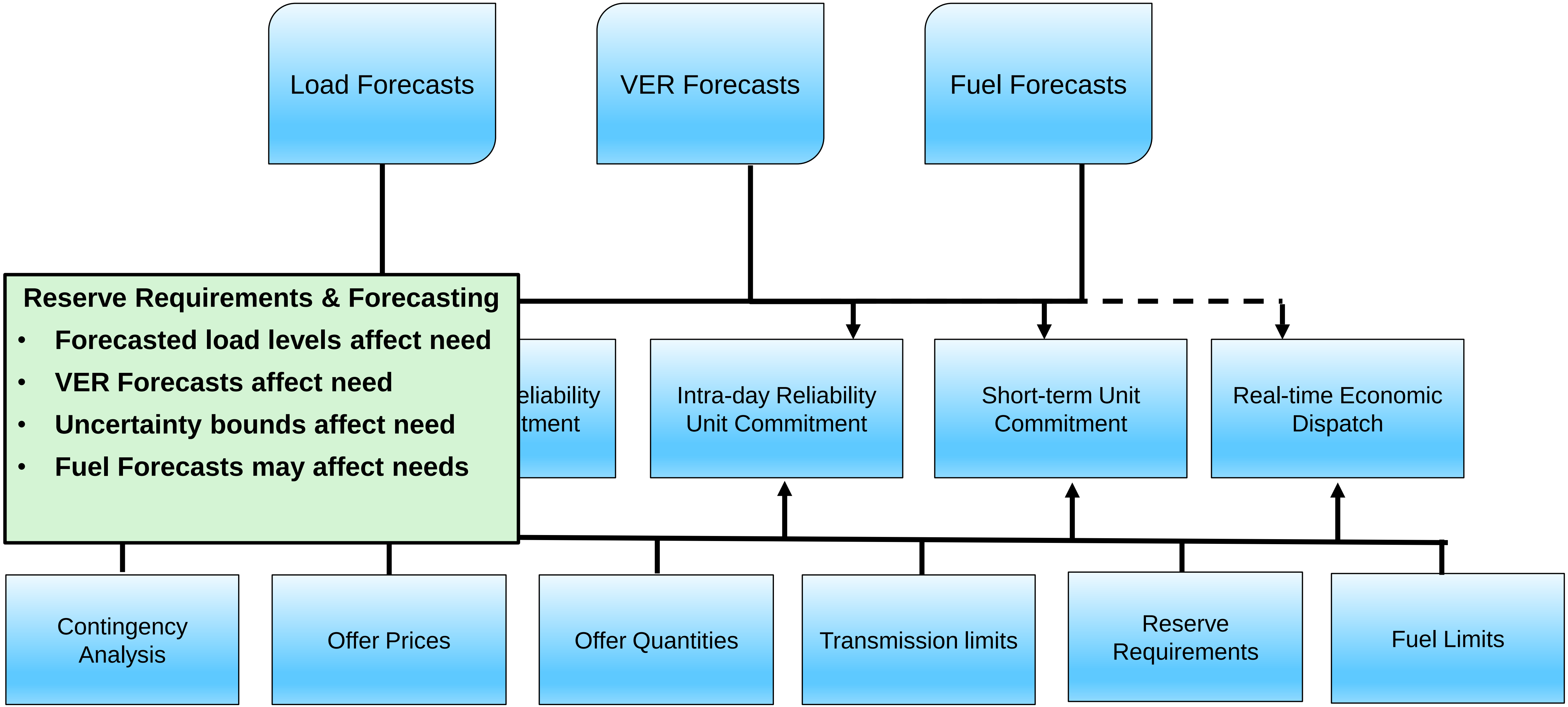
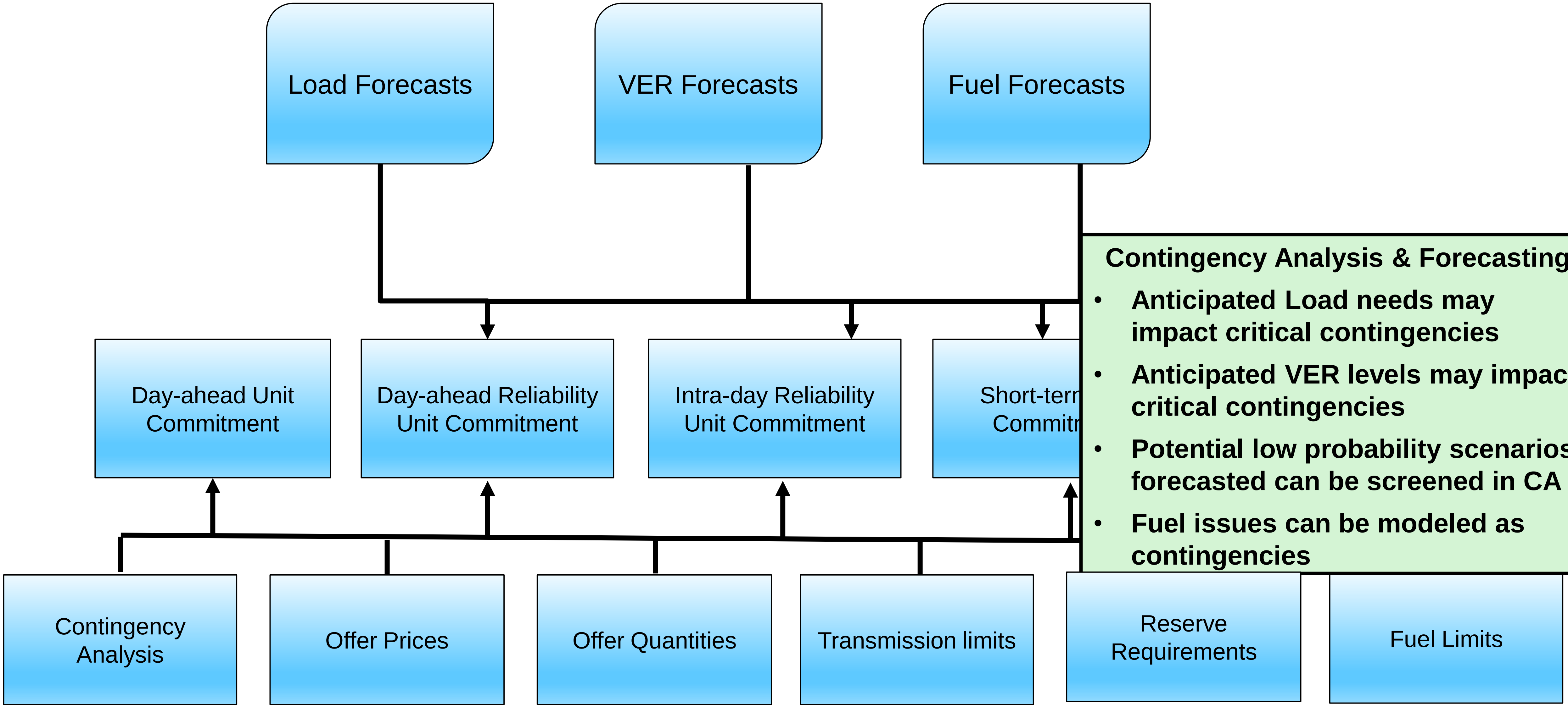
Evolution of Forecasting Applications



Evolution of Forecasting Applications (Reserve Rqmnts)



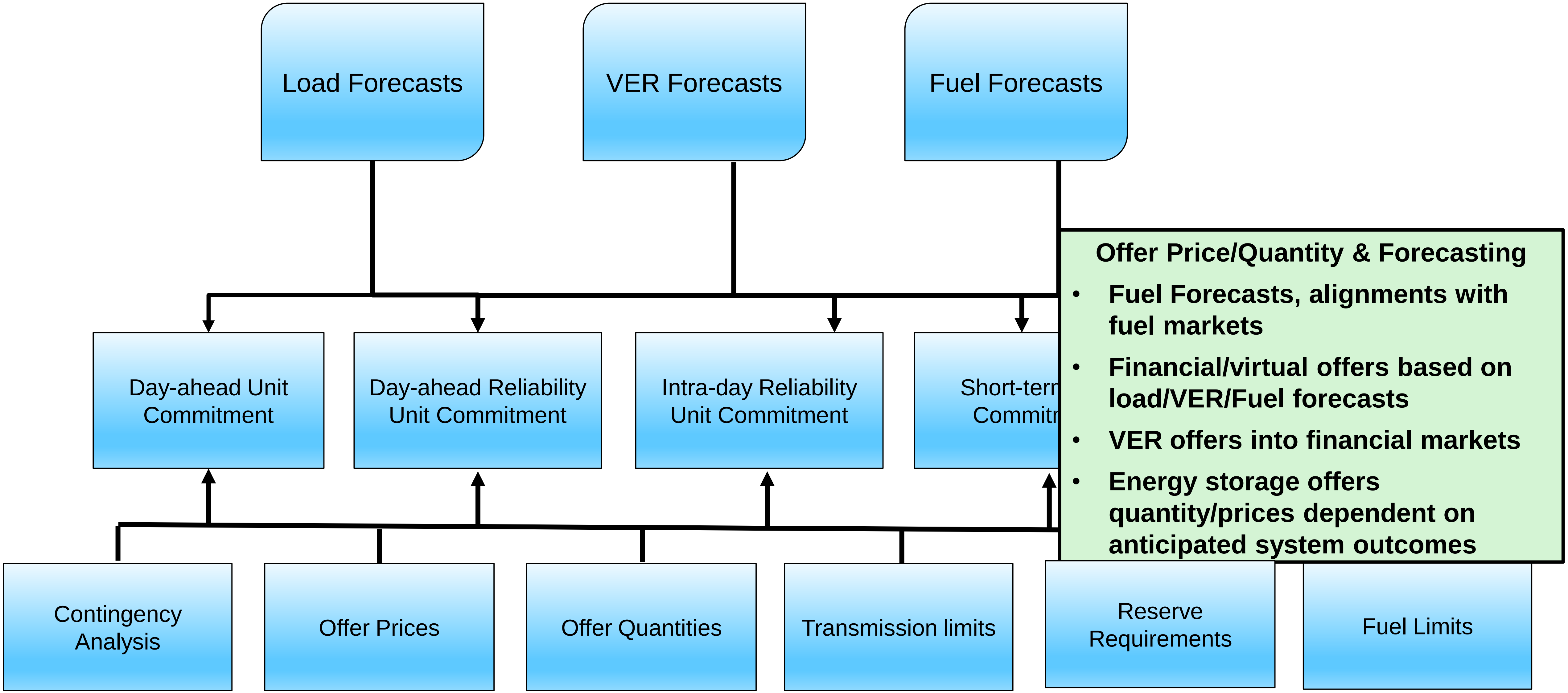
Evolution of Forecasting Applications (Contingency Analysis)



Contingency Analysis & Forecasting

- **Anticipated Load needs may impact critical contingencies**
- **Anticipated VER levels may impact critical contingencies**
- **Potential low probability scenarios forecasted can be screened in CA**
- **Fuel issues can be modeled as contingencies**

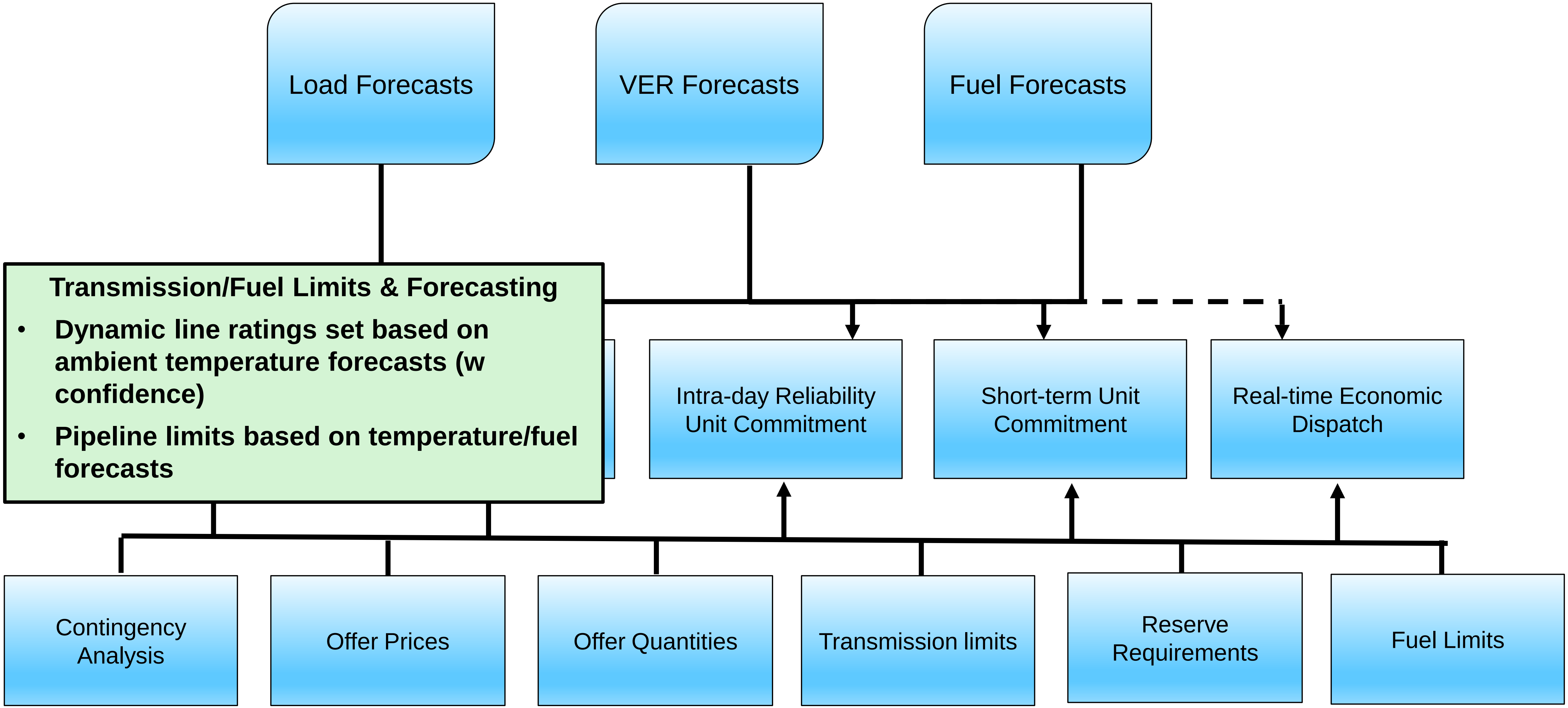
Evolution of Forecasting Applications (Offer Price/Quantities)



Offer Price/Quantity & Forecasting

- **Fuel Forecasts, alignments with fuel markets**
- **Financial/virtual offers based on load/VER/Fuel forecasts**
- **VER offers into financial markets**
- **Energy storage offers quantity/prices dependent on anticipated system outcomes**

Evolution of Forecasting Applications (Transmission Limits)



Transmission/Fuel Limits & Forecasting

- **Dynamic line ratings set based on ambient temperature forecasts (w confidence)**
- **Pipeline limits based on temperature/fuel forecasts**

Energy Storage Operation

- FERC Order 841 and other state/regional initiatives may allow further adoptions of energy storage
- ISO management of state of charge not required
- VER, load, fuel forecasts critical for:
  - Energy storage market participation (offer price, quantities)
  - Reliability (ensure sufficient generation to meet conditions)

Long-term forecasting

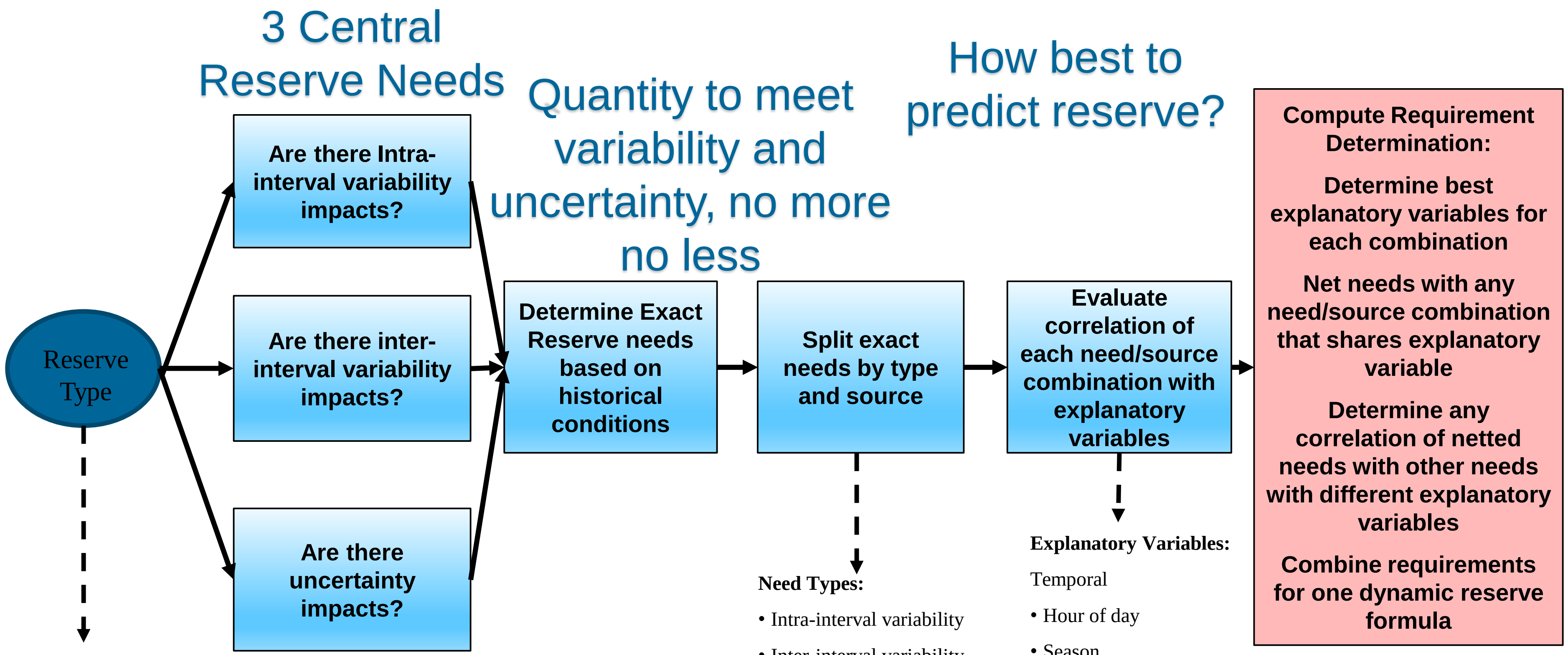
- System adequacy
- Outage scheduling
- Extreme event forecasting
- Revenue forecasting
- Policy forecasting

Reserve Forecasting

Dynamic Reserve Method Overview

- Method that utilizes a dynamic reserve method that attempts to best predict exact reserve need with some level of confidence
- Exact need: Review historical data and evaluate historical need based on the intra-interval variability, inter-interval variability and uncertainty
- Determine explanatory variables that best predict reserve need
- **<u>Forecast</u>** operating reserve need using **<u>forecast</u>** data and other explanatory variables
- Requirement combines all reserve needs and var./unc. sources to provide a reserve requirement formula based on one or more look up tables
- Choice of confidence interval allows user flexibility to choose risk tolerance and economic efficiency objectives of balancing area

Dynamic Reserve Requirement Methodology



Reserve Type Information:

- Scheduling Process where Reserve is held
- Scheduling Process where Reserve is released
- Reserve need met
- Direction (up/down/both)

Reserve Defined by how the BA schedules resources

Need Types:

- Intra-interval variability
- Inter-interval variability
- Uncertainty

Sources:

- Wind
- Solar
- Load
- Imports
- Self-schedules, start-up, shutdowns

Explanatory Variables:

Temporal

- Hour of day
- Season
- Weekday/weekend

Production-based

- Production level
- Delta production forward
- Delta production backward
- Absolute Delta

More advanced methods: multi-variable, neural networks, autogressive

Forecast for total reserve need

Example Combination of Needs to Determine Requirement

Wind Uncertainty Need

Wind Production	Reserve Need (multiplier)
0	0.59
42.35	0.90
84.7	0.93
127.05	0.92
169.4	0.95
211.75	0.87
254.1	0.88
296.45	0.91
338.8	0.94
381.15	0.93
423.5	0.87
465.85	0.93
508.2	0.84
550.55	0.83
592.9	0.91
635.25	0.83
677.6	0.76
719.95	0.61
762.3	0.43
804.65	0.41

Wind Variability Need

Absolute value of P(t)-P(t-1) of wind power	Reserve need (MW)
0	25.31
31.85	59.24
63.7	76.90
95.55	93.10
127.4	127.67
159.25	143.55
191.1	169.54
222.95	176.99
254.8	208.63
286.65	202.73
318.5	263.91
350.35	235.30
382.2	269.80
414.05	236.74
445.9	381.98
477.75	282.54
509.6	452.25
541.45	150.27
573.3	45.42
605.15	177.41

Load/solar Var.&Unc. Need

Hour of day	Reserve Need (MW)
0	253.587
1	186.767
2	105.5
3	48.159
4	59.237
5	155.482
6	272.777
7	482.856
8	326.674
9	218.692
10	161.407
11	165.684
12	200.067
13	239.633
14	307.825
15	249.94
16	298.355
17	314.712
18	191.929
19	289.295
20	463.521
21	542.266
22	485.006
23	373.468

Correlation wind uncertainty and wind variability = -0.14;

$$ReserveRequirement_{t\_h} = \sqrt{\sum_{n=1}^{N} f_n(ExVar_{t\_h})^2 + 2 * \sum_{n=1}^{N} \sum_{j=1, j\neq k}^{N} \rho_{n-k} * f_n(ExVar_{t\_h}) * f_k(ExVar_{t\_h})}$$

Hawaiian Electric Company Dynamic Reserve Study Results

Week	Reserve	Adjusted Cost ($M)	Sigma ACE (MW)	HECO Compliance (%)	Head Room Deficiency (%)
Spring A	Existing Must Run	11.913	4.95	94.3	0.0
	No Reserve	11.081	4.77	94.2	9.6
	Existing Method	11.374	4.93	94.2	0.0
	EPRI 90%	11.281	4.87	94.3	0.0
	EPRI 75%	11.240	4.81	94.5	0.6
Spring B	Existing Must Run	13.167	4.47	95.1	0.0
	No Reserve	12.620	4.21	96.0	5.5
	Existing Method	12.834	4.25	95.8	0.8
	EPRI 100%	12.800	4.23	95.9	0.0
	EPRI 95%	12.781	4.23	95.9	0.0
Summer A	Existing Must Run	13.578	5.18	93.6	0.0
	No Reserve	13.125	5.12	94.2	3.2
	Existing Method	13.287	5.10	94.0	0.1
	EPRI 90%	13.241	5.07	94.1	0.0
	EPRI 75%	13.211	5.09	94.1	0.0
Summer B	Existing Must Run	13.910	3.89	96.4	0.0
	No Reserve	13.559	3.65	97.0	3.4
	Existing Method	13.683	3.68	97.0	0.6
	EPRI 90%	13.655	3.64	97.0	0.0
	EPRI 75%	13.652	3.63	97.0	0.0

Week	Reserve	Adjusted Cost ($M)	Sigma ACE (MW)	HECO Compliance (%)	Head Room Deficiency (%)
Fall A	Existing Must Run	14.291	3.81	96.5	0.0
	No Reserve	13.967	3.62	97.0	2.1
	Existing Method	14.095	3.60	97.0	0.0
	EPRI 90%	14.083	3.61	97.0	0.0
	EPRI 75%	14.058	3.61	97.0	0.0
Fall B	Existing Must Run	14.040	3.07	97.9	0.0
	No Reserve	13.667	2.87	98.1	3.9
	Existing Method	13.763	2.91	98.1	1.3
	EPRI 90%	13.758	2.85	98.1	0.0
	EPRI 75%	13.748	2.85	98.2	0.0
Winter A	Existing Must Run	13.073	3.21	97.7	0.1
	No Reserve	12.506	3.02	98.1	4.9
	Existing Method	12.658	3.09	98.0	2.0
	EPRI 90%	12.613	3.03	98.1	0.0
	EPRI 75%	12.603	3.06	98.1	0.1
Winter B	Existing Must Run	12.188	5.86	93.1	0.0
	No Reserve	11.358	5.66	93.3	11.0
	Existing Method	11.570	5.97	93.0	0.8
	EPRI 90%	11.527	5.76	93.1	0.0
	EPRI 75%	11.515	5.69	93.5	0.5

Dynamic Reserve with 90% confidence interval allows for cycling of units with constant or improvement to reliability at $21M savings

Lower confidence interval provides greater reliability than existing methods at greater cost savings

Probabilistic Forecasting Applications

Application	Description	In use?
Stochastic Scheduling (STUC)	Committing or dispatching resources to meet multiple potential scenarios based on minimizing the expected cost	N/A
Robust optimization-based Unit commitment and dispatch	Similar to STUC, but only using the “worst case” scenario to ensure the decisions are robust towards those situations	N/A
Do Not Exceed Dispatch VER Limits	Using probabilistic forecasts to determine the likelihood of VER providing greater energy than expected that can exceed balancing capabilities or network limit violations	ISO-NE
Outage Planning	Using long-term probabilistic forecasts to determine whether it is optimal to take certain units (including non-renewable ones) or transmission facilities out for maintenance when it is likely they are not needed and economic losses are minimal	N/A
Energy Market Trading (E.g., virtual trading)	Using potential scenarios and probability of those scenarios to assist in taking financial positions within the market (either as a VER, load, or virtual trader). Longer term probabilistic forecasts can also be used for long-term markets, like financial transmission rights.	Yes
Level of frequency response	Using probabilistic forecasts to understand the level of frequency response (or synthetic inertia) a wind plant or collection of wind plants can provide	N/A

Others: Real-time contingency analysis, topology switching, reserve scheduling

Use of Probabilistic Forecast directly in scheduling

Stochastic SCUC/ED

Multi scenario-based, expected cost minimized

L. Wu et al., 2007;
Bouffard et al., 2008;
Morales et al., 2009;
Ruiz et al., 2009;
Meibom et al., 2011

Chance Constrained SCUC/ED

Feasibility

satisfied by pre-determined probability level

Ozturk et al., 2004;
Q. Wang et al., 2012;
H. Wu et al., 2014

Worst case only scenario-based

Robust SCUC/ED

Immunity against all realization, worst case cost minimized

Bertsimas et al., 2013;
Zhao et al., 2013

Interval SCUC/ED

Upper- and lower-bound feasible, only expected operation minimized.

J. Wang et al., 2007;
Y. Wang et al., 2011;
L. Wu et al. 2012

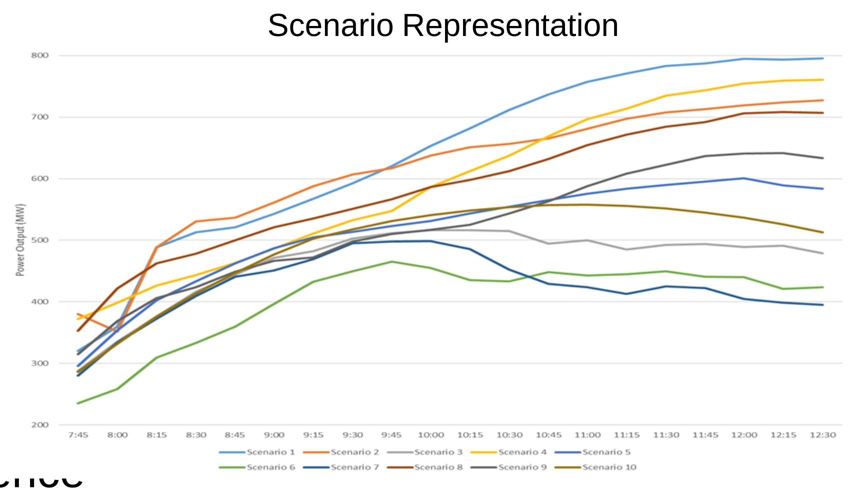
Dynamic Reserve

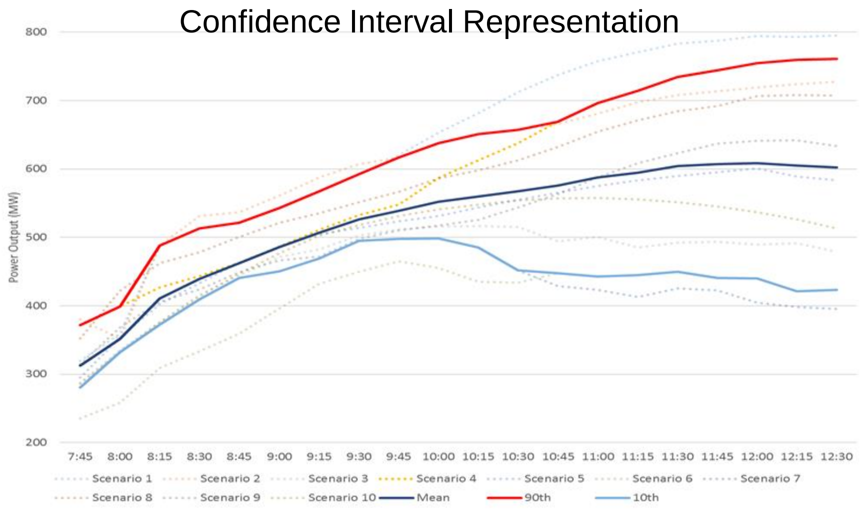
Scenarios define exogenous deterministic constraints

Ortega-Vazquez et al, 2007;
Matos et al., 2011;
Ela et al., 2011 (summary);
Ibanez et al., 2013

Probabilistic Forecasting Applications

- Use of probabilistic forecast open doors to new applications and implementations of forecast informati
- Multiple manners to determine uncertainty:
  - Run models with variation in the inputs that have uncertai
  - Run different weather or power conversion models
  - Statistical analysis based on previous results (analog)
  - Can be displayed in numerous manners, including confide intervals, scenarios, distributions, etc.





- Being used in practice for a number of regions – exam include
  - Spain (REE): confidence intervals set reserve requireme
  - Swissgrid: stochastic optimization for week ahead reserv procurement based on generator availability and cost
  - ERCOT: wind ramping forecast

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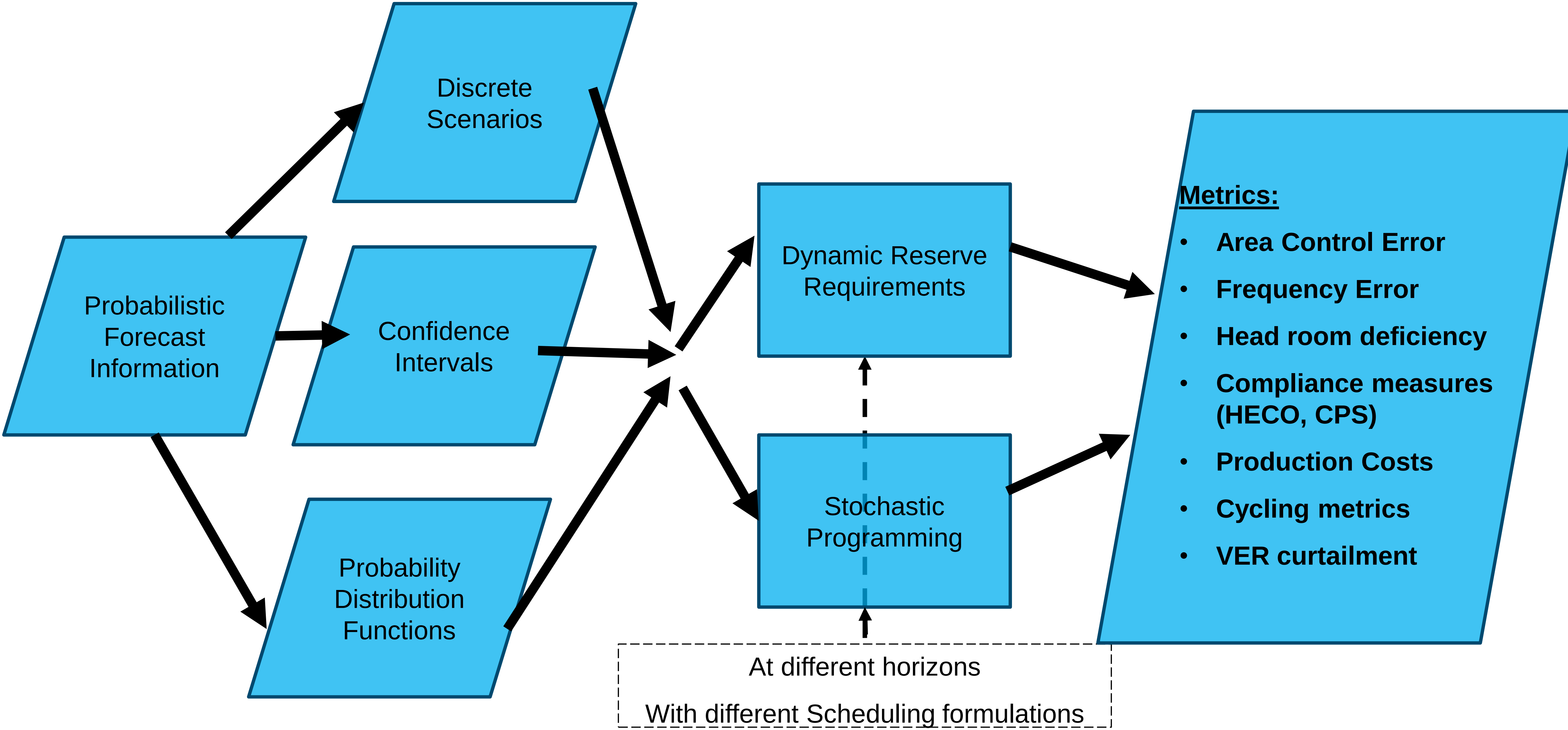

Summary

- Forecasting of many different aspects of power system gaining importance
- Forecasts of VER, load, fuel availability used differently in operational scheduling
- Long-term forecasting becoming more important with greater uncertainties
- Application of forecasting reserve important for reliability
- Use of probabilistic forecasts provide additional potential benefits and applications

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